ESSAYS ON BANKING AND FINANCIAL STABILITY

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ABSTRACT

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Financial crises have occurred repeatedly throughout history in both high and middle-to-low income countries. This dissertation studies how the interactions of financial market participants affect financial stability. In the first part of the dissertation, I analyze sales of assets between financial institutions in the United States and find evidence consistent with the theory that credit-constraints affect the demand for, and price of, assets sold in fire-sales. In the second part, I document the empirical regularity that the correlation of banks' stock return – a measure of the interconnectedness of banks – increases in the run up to banking crises and thus helps predict crises. The third part finds that the main measure of asset risk-exposure that banks report to regulators are thought to be credible by equity investors, but less so in countries where regulators have allowed banks more discretion over the calculation of the measure.

BIOGRAPHICAL SKETCH

Sonali Das is a PhD candidate in the Department of Economics at Cornell University, with research interests in international finance and banking. During the course of her doctoral studies, she has interned at the International Monetary Fund, the Federal Reserve Bank of San Francisco, and the Brookings Institution. Sonali holds an MA from McGill University (2005, Economics) and a BSc from the University of Toronto (2004, Economics and Statistics). Sonali was born and raised in Moncton, Canada.

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Chapter 1

Introduction

Economists have long struggled with the question of how to structure financial systems to achieve an efficient allocation of resources and allow agents to share risk. They key impediment lies in the fact that financial markets are prone to panics that can be self-fulfilling and contagious, magnifying the consequences of shocks that hit few institutions or markets. Over the last two centuries, there has been only a single year in which no country was experiencing a financial crisis.[1] This dissertation studies a component of financial markets often overlooked in economics – how financial market participants interact with each other – and its implications for financial stability.

In the second chapter, I analyze how the equity capital position of financial institutions affects their demand for assets and the resulting value of

[1] The year being 1823. According to Reinhart and Rogoff's (2009) history of financial crises for 69 countries, several countries have had a financial crisis (banking crisis, currency crisis, and/or external debt crisis) in each year since 1800. The average number of countries in crisis in each year of this period is 14.

transactions between financial institutions. When intermediaries are credit-constrained and have a sudden need for liquidity, they are forced to sell assets to other institutions for cash. My results show a positive relationship between buyer capital and the likelihood of buying assets, and between buyer capital and the value of the deal. That is, those institutions that are the least constrained in their ability to raise funding are those that demand assets and pay more for them. This result does not hold, however, for deposit-taking institutions that had access to several government programs designed to improve their funding situation during the crisis of 2008.

The third chapter takes a broad view and documents a new empirical regularity in the run up to banking crises. In a sample of 45 countries, covering the period from 1993 to 2009, the correlation of banks' stock returns increases before the onset of a crisis. The increase in the correlation measure is not driven by an overall increase in the national stock market – i.e. it does not simply capture 'boom' periods – and there is no significant relationship between the correlation of non-financial firms and crisis. Thus the stock return correlation can be seen as a simple measure of interconnectedness among banks that helps predict banking crises.

The fourth chapter, written jointly with Amadou N.R. Sy, focuses on banks – regulated, deposit-taking institutions – and studies market perceptions of the riskiness of their risk-weighted assets (RWA) by examining the determinants of the stock returns of an international panel of banks. Banks are required to hold capital as a percentage of RWA and the rules used to calculate RWA have changed over time, allowing banks more discretion over the calculation. We find a negative relationship between RWA and stock returns over periods of financial crisis, suggesting that investors believe RWA are an indication of bank portfolio risk. This relationship is weaker in countries that had implemented Basel II before the onset of the crisis, allowing banks to use internal risk models to assess credit risks.

Chapter 2

The Effect of Leverage on Asset Sales between Financial Institutions: Deal Level Evidence

2.1 Introduction

In times of crisis, financial institutions are often forced to sell assets in order to stay solvent. While this may be a necessary strategy for an individual institution facing borrowing constraints, the action of selling under duress can in fact drive down the price of assets and deepen the crisis. There is a growing literature on these fire-sales of assets, and their role in deepening financial instability (Shleifer and Vishny 2011). Shleifer and Vishny (1992) first formalized the idea of the 'fire-sale' pointing out that asset liquidation often happens when the best users are (also) credit constrained, leading to a lower liquidation value.

This paper provides new evidence on asset transactions between financial institutions. I first examine how the capital position of potential buyers of assets affects both their decision to purchase and the value of transactions themselves. There are two main features to recent theoretical contributions that model fire-sales as an amplifying mechanism of liquidity crises (Brunnermeier and Pederson (2009), Krishnamurthy (2010), and Fostel and Geanakoplos (2008) in a multiple asset setting). First, the amount of funding available to financial intermediaries is a function of their equity capital, up to a maximum amount; and second, the demand for assets is a function of the total funds available to intermediaries. These models focus on the constraints of the sellers and sales are assumed to be absorbed by agents who have lower valuations of the assets. The 'cash-in-the-market' pricing models of Allen and Gale (1998, 2005) explicitly model the buyers, however, and show that an asset's sale price will be determined by the limited amount of cash, or liquidity, held by the surviving financial intermediaries, since they are the marginal buyers. I find that the capital to assets ratio of financial institutions is positively related to both their decision to purchase assets and to the value of the transaction.

Second, I analyze whether there are sectoral[1] differences in how buyer capital affects the demand for assets and the deal value. Based on their relationships before the subprime crisis, and government policies implemented during the crisis, different types of financial institutions have had varying degrees of access to funding over the past few years. He, Khang, and Krishnamurthy (2010) carefully measure how securitized assets shifted across sectors in the United States during the 2008 crisis. They find that the hedge fund and broker-dealer sectors, sectors that rely on repo financing, reduced asset holdings and the commercial banking sector, which had access to more stable funding sources, increased asset holdings. Their evidence suggests that certain groups of financial institutions can step in to ease liquidity problems during financial crises, but also that government liquidity policies implemented to encourage commercial banks to lend to the real sector may have unintended effects. By disaggregating to the institution level in this paper, I am able to shed light on the extent to which credit constraints affect asset demand and price across institutions that are similarly affected by policy.[2]

I focus on the potential buyers of assets, as opposed to the sellers, for two reasons. First, distressed financial institutions sell assets for reasons that are fairly well understood. When in need of liquidity, they have three options:

[1]By 'sectoral' I mean sub-sectors within the financial sector. Broadly: deposit-taking institutions (commercial and savings banks), investment banks, broker-dealers, hedge-funds, and real estate and insurance companies.

[2]He, Khang, and Krishnamurthy (2010) study securitized assets while I study assets such as property and actual loan portfolios held by financial institutions. More detail is provided in the data description in section 2.3.

raise equity capital, raise debt, or sell assets for cash. Raising equity capital is thought to be costly due to debt overhang (Myers 1977) or adverse selection problems facing the potential equity investors (Myers and Majluf 1984) even in good times, so it is likely to be especially difficult or costly in times of financial distress. Acharya, Gujral, and Shin (2009) find that financial intermediaries did raise new capital in 2008, both from private investors and from government-funded capital injections, but it was predominantly in the form of hybrid claims such as preferred equity and subordinated debt. That is, claims that are debt-like and cannot be thought of as equity capital. Second, the information on sellers of assets in the database used is less detailed and complete than that on the buyers, making an analysis of the sellers' balance-sheets difficult.[3] The next section describes differences in access to funding across financial sectors, sections 2.3 and 2.4 describe the data used in the analysis and the estimation strategy, sections 2.5 and 2.6 present the results and robustness checks, and section 2.7 concludes.

2.2 Access to funding within the financial sector

Funding composition differs across different types of financial institutions. The first distinction, in all periods and not just during crises, is that commercial and savings banks raise (partially) insured deposits, which are considered to be a relatively stable and cheap form of borrowing. Runs on banks

[3]For example, when a real-estate property is being sold the database often lists the name of the selling company as simply the address of the property being sold. Identifying information for the buyers is properly recorded, however.

by depositors have been relatively rare in the United States since the creation of the Federal Deposit Insurance Corporation (FDIC) in 1934.[4] Additionally, coverage limits – the amount per depositor that is insured by the FDIC – were increased from \$100,000 to \$250,000 in 2008. A second policy affecting commercial banks was the Temporary Liquidity Guarantee Program (TLGP), in place from October of 2008 to December of 2010. It allowed deposit-taking institutions to issue senior unsecured debt with a maximum three year term, with the FDIC insuring default on these bonds for a fee of 25 to 50 basis points. Finally, the Fed cut the discount rate for commercial banks several times beginning in August 2007.

The Fed also allowed investments banks to begin borrowing directly from the discount window in March of 2008, using a broad range of debt securities as collateral. Hedge funds and broker-dealers, on the other hand, did not have access to government support and traditionally raise debt mostly in the form of repo financing. These differences in funding sources suggest that deposit-taking institutions had greater access to, or a lower cost of, funding, followed by investment banks, and then hedge-funds and broker-dealers.

[4]Prior to the crisis of 2008, some academic economists declared depositor bank runs to be dead after the implementation of deposit insurance, while others pointed to the runs that took place in emerging market economies in which there was deposit insurance in place. This crisis saw a resurgence of bank runs – first with Northern Rock in the UK and then BearStearns and IndyMac in the United States, in September 2007, March 2008, and July of 2008.

2.3 Data

The main dataset used in the analysis is the Thomson Reuters SDC Platinum M&A database, which contains data on mergers and acquisitions of firms, as well as on sales of assets. The assets traded are primarily real estate portfolios (apartment buildings, office buildings, etc.), loan portfolios, bank branches or units of financial institutions, and there are a few observations on other assets such as equity investment portfolios, asset-backed securities, and IT systems. The type of asset is not given by data providers, unfortunately, so these were coded from a text description of the deal where possible.[5] I analyze deals between financial institutions located in the United States between 2005 and 2011, where the buyer is a publicly-traded company. Approximately 85% of the assets sold by US institutions to other financial institutions in this time period are to other US institutions.[6]

To estimate a model that controls for sample selection bias arising from the possibility that a firm's characteristics affects its decision to buy assets, I first start with the universe of publicly-traded financial firms in United States that are contained in the Worldscope/Datastream database. Financial firms are those with a Standard Industrial Classification code beginning with the

[5] The description of the deal was searched for strings such as: "home loan portfolio"; "real estate portfolio", "acquired" and "bank" and "branches"; "asset backed securities", etc. covering all the possible types.

[6] Another 6% are sold to Australian and Canadian firms, and the remaining deals are made with the following 13 countries: Belgium, France, Germany, Ireland, Israel, Japan, Mexico, Netherlands, South Korea, Spain, Switzerland, United Kingdom, and United Arab Emirates.

digit 6 (division H). The focus on publicly-traded firms is driven primarily by data constraints, as the Worldscope database only contains balance-sheet data for public firms. The sample of potential buyers consists of 1116 financial firms. This sample of potential buyers is then merged to the deals with publicly-traded buyers in the deals database. The resulting sample is of 402 deals, representing 402 'sellers' and 183 unique buyers.

2.4 Modeling the determinants of asset transaction values

The main hypothesis being tested in this paper is that there is a positive relationship between the capital to assets ratio of the buyer, and the value of an asset sale.[7] There are two reasons to expect this. First, an institution's cash is counted in its capital measure, so firms with higher capital may simply have higher cash on hand with which to purchase assets and may have a higher willingness to pay for assets. Second, since capital ratios are often seen as a measure of health for financial institutions, those with more capital should be able to borrow on better terms. The leverage constraint theories of Brunnemeier and Pederson (2009) and Fostel and Geanokoplos take the maximum debt financing available to an intermediary to be proportional to its equity capital. A second hypothesis concerns the intensity of the relationship between firm capital and deal value. As leverage constraints are more

[7] By which I mean the price at which the asset is sold. I use the term 'deal value' instead of 'price' simply to make clear that the units of the assets being sold are not standardized.

important for non-deposit taking institutions, we expect the positive relationship between buyer capital and deal value to be greater for non-deposit taking institutions.

To test these hypotheses, I use a Heckman selection model (Heckman 1979) to estimate the effect of buyer capital on the value of an asset sale. Under the assumption that any unobservable characteristics that affect a financial firm's decision to buy assets are uncorrelated with unobservable characteristics that affect the value of the deal itself, ordinary least squares would produce unbiased estimates of the effect of buyer capital on the value of an asset sale. This is too strong an assumption to make, however, as one can imagine the preferences of a manager inclined to expand during crisis times to affect his approach to bargaining on price. In addition, the effect of a buyer's characteristics on its propensity to purchase an asset is interesting in itself.

Let i=seller, j=buyer, and $E_{jt} = 1$ if institution j buys an asset in year t. The first stage selection equation is a Probit estimation of the probability that a buyer purchases an asset in a given year of the sample.

$$\Pr(E_{jt} = 1) = F(\delta_1(capital_{jt}/A_{jt}) + \delta_2 \log A_{jt} + \delta_3 Agrowth_{jt} + \delta_4 \log mrkttobook_{jt} + v_t) \tag{2.1}$$

where the buyer's capital to assets ratio, $capital_{jt}/A_{jt}$, and size, given by the log of assets, are variables of interest in both the selection equation and the main equation. Two other buyer characteristics, asset growth and the log of the market-to-book ratio, are included to identify the selection equation. $Agrowth_{jt}$ is the buyer's percentage increase in total assets over the previous year and $mrkttobook_{jt}$ is the market value of a firm's assets divided by the book value of its assets.[8] The first variable captures whether the firm has been expanding and the second the firm's potential to grow. Year dummies are included to control for macroeconomic shocks that affect all financial institutions alike. The expected signs of the coefficients are $\delta_1 > 0, \delta_2 > 0, \delta_3 > 0$, and $\delta_4 > 0$. That is, institutions with more capital, larger institutions, institutions that have been expanding, and institutions with a higher Tobin's q, are expected to be more likely to purchase assets.

The estimated coefficients from equation 2.1 are used to calculate the inverse Mills ratio, $\phi(\delta)/\Phi(\delta)$, which is then included in the main equation to correct for potential sample selection bias. The equation estimating the determinants of the value of asset sales is:

$$\log y_{ijs} = \beta_1(capital_{jt}/A_{jt}) + \beta_2 \log A_{jt} + \theta_1 X_{ij} + \theta_2 MarketR_s + \lambda(\phi(\delta)/\Phi(\delta)_{jt}) + u_{ijt} \tag{2.2}$$

The dependent variable $\log y_{ijs}$ is the log of the value of a transaction between seller i and buyer j that takes place on day s of year t, in millions of US dollars. The selection equation 2.1 is estimated using a buyer-year panel, while equation 2.2 is estimated on a pooled sample of deals with selection bias correction at the buyer-year level. The main explanatory variable of interest

[8] Calculated as (market value of equity + book value of liabilities)/book value of assets. This is standard practice in the corporate finance literature.

is the capital ratio, and the hypothesis is that $\beta_1 > 0$. We also expect $\beta_2 > 0$ as larger firms are likely to buy larger assets. The control variables included in X_{ij} are indicator variables that denote whether the seller and buyer are in the same US city, the same US state, and the same sector. $MarketR_s$ is the stock market return over the month prior to the day the deal is announced, included to control for macroeconomic shocks.

Table 2.1 provides descriptive statistics corresponding to both the full sample of equation 2.1 and the deal (censored) observations. We see that institutions that buy assets have a high capital ratio on average, at 71 percent, compared to 31 percent for all firms. The firms that buy assets are also larger.

Table 2.1: Descriptive statistics

Descriptive statistics

	Uncensored (5823 obs)		Censored/deal (402 obs)	
	Mean	Std Dev	Mean	Std Dev
Deal value, millions of US dollars			350.75	1551.44
Buyer capital/assets	31.28	26.52	71.02	31.11
Buyer assets, millions of US dollars	20,600	145,000	67,700	295,000
Asset growth (%), previous year	10.63	22.63	17.49	27.12
Buyer market to book	0.56	1.52	1.08	0.73
US stock market return, previous month			0.54	4.61
Same city			0.04	0.20
Same state			0.28	0.45
Same sub-sector			0.27	0.02

2.5 Results

I find evidence in support of the hypothesis that the value of a deal is increasing in the buyer's capital ratio. Table 2.2 presents the estimation of equation 2.2 using OLS (not including the sample selection correction term), for the sake of comparison with the Heckman selection model.

Table 2.2: Determinants of value of asset sale – OLS

Dependant variable: log(Value of asset sale)

	(1) log(deal value)
Buyer capital/assets	0.016***
	(0.003)
Buyer log(assets)	0.578***
	(0.037)
Same city	0.223
	(0.354)
Same state	0.187
	(0.154)
Same sub-sector	0.888***
	(0.204)
US stock market return	0.004
	(0.014)
Observations	402
Adj R-squared	0.390

This table presents the estimation of the deal value equation using OLS. The dependent variable is the log of the value of the transaction, in millions of US dollars. The explanatory variables are the buyer's total capital to assets ratio, the buyer's size given by the log of total assets, indicator variables for whether the seller and buyer are based in the same city, same state, and whether they belong to the same sub-sector, and the US stock market return over the month prior to the day the deal is announced. Standard errors are in parentheses below the coefficient estimates. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

The coefficient on the capital ratio is the estimated semi-elasticity of the deal value with respect to the capital ratio. The estimate of 0.016 indicates that a 1 percentage point increase in the capital ratio is associated with a 1.6 percent increase in deal value. The coefficient on the size variable indicates that a 1 percent increase in the size (assets) of the buyer is associated with a 0.6 percent increase in the deal value, on average. Whether the seller and buyer are located in the same US city or state seem not to affect the value of the deal, but deals between firms in the same financial sector have a higher value, with the coefficient of 0.888 indicating they are priced higher by 2.43 million US dollars on average.

Table 2.3 shows the benchmark estimation results of the Heckman selection model. The estimated coefficients in column (1) show that the capital ratio, size, and asset growth of the buyer are positively related to its propensity to buy assets. The marginal effects are as follows: a 1 percentage point increase in the capital ratio (from the mean) increases the probability of a deal by 0.8 percent, a 1 percent increase in size increases the probability of a deal by 0.05 percent, and a 1 percentage point increase asset growth increases the probability of a deal by 0.06 percent.

The positive coefficient lambda in column (2) indicates that unobservables in equations 2.1 and 2.2 are positively correlated.[9] That is, unobserved characteristics that increase a financial institution's likelihood of buying assets also increase the value of the deal. This coefficient is statistically significant at the 5 percent level, indicating that there is indeed a sample selection effect and OLS is not an appropriate method to estimate equation 2.2. Once we correct for the selection bias, the effect of capital on deal value is higher: 3.2

[9]The correlation between the error terms is in fact ρ where $\rho = \lambda/\sigma$ and σ is the variance of the error term in equation 2.2, u_{ijt}.

Table 2.3: Determinants of deal probability and deal value

Heckman selection model

	(1) probability(deal)	(2) log(deal value)
Buyer capital/assets	0.026***	0.032***
	(0.002)	(0.008)
Buyer log(assets)	0.178***	0.695***
	(0.014)	(0.062)
Same city		0.157
		(0.351)
Same state		0.180
		(0.152)
Same sub-sector		0.872***
		(0.199)
US stock market return		0.007
		(0.014)
lambda		0.778**
		(0.337)
Buyer asset growth	0.002*	
	(0.001)	
Buyer log(market to book)	-0.032	
	(0.057)	
Observations	5823	402

This table presents the results of estimating the Heckman selection model. Column (1) shows the selection equation. The explanatory variables are the buyer's total capital to assets ratio, the buyer's size given by the log of total assets, the US stock market return over the month prior to the day the deal is announced, the buyer's growth in assets in the year prior to the deal, and the log of the buyer's market value of assets to book value of assets. Column (2) shows the deal value equation. The explanatory variables are the buyer's total capital to assets ratio, the buyer's size, indicator variables for whether the seller and buyer are based in the same city, state, whether they belong to the same sub-sector, the selection correction terms, and year dummies (not shown).

percent for a 1 percentage point increase in capital/assets compared to the 1.6 percent for the OLS results in Table 2.2.

Next, I group the sample (buyers) into deposit-taking institutions and 'non-deposit-taking' institutions, and include interaction terms for the non-deposit-taking institutions in the estimation. Table 2.4 shows the results. We see that it is the non-deposit-taking institutions that account for the positive relationship between buyer capital and both the likelihood of buying assets and the deal value. This is consistent with the hypothesis that the capital position of deposit-taking institutions should not affect their asset purchases as much as other institutions, as the deposit-taking ones had better access to or cheaper funding during the crisis.

The next specification digs further into the differences between different financial sub-sectors. Tables 2.5 and 2.6 provide further descriptive statistics on the types of financial institutions. Table 2.7 shows the estimation results including interaction effects for each group of non-deposit-taking institutions: investment banks and other credit institutions, hedge funds and broker-dealers, and insurance and real estate. The results show no relationship between capital, the likelihood of making a purchase, and the deal value for deposit-taking institutions. There is a significant and positive relationship between capital and the probability of making a purchase for each other type of potential buyer, however. Column (2) shows no relationship between capital and deal value for each group, and no significant differences across sectors.

Table 2.4: Determinants of deal probability and deal value – Deposit-taking institutions versus other financial institutions

Heckman selection model

	(1) probability(deal)	(2) log(deal value)
Buyer capital/assets	-0.014*	-0.005
	(0.008)	(0.014)
Buyer capital/assets * non-deposit taking	0.042***	0.033***
	(0.009)	(0.011)
Buyer log(assets)	0.198***	0.718***
	(0.028)	(0.062)
Buyer log(assets) * non-deposit taking	0.004	-0.001
	(0.004)	(0.003)
Same city		0.153
		(0.347)
Same state		0.205
		(0.151)
Same sub-sector		0.884***
		(0.197)
US stock market return		0.006
		(0.014)
lambda		0.840**
		(0.331)
Buyer asset growth	-0.002	
	(0.003)	
Buyer log(market to book)	0.345*	
	(0.177)	
Observations	5823	402

This table presents the results of estimating the Heckman selection model, including an interaction term for financial institutions that do not raise deposits (indicated by '* non-deposit taking'). The other explanatory variables are as in Table 2.3.

Table 2.5: Number of transactions between financial sectors

	Buyers				
Sellers	Deposit inst	Inv bank & oth	HF & BD	Ins & real est	Total
Depositary institutions	51	2	1	0	54
Inv bank & other credit	10	18	6	0	34
Hedge fund & broker-dealers	4	9	15	0	28
Insurance & real estate	2	3	255	26	286
Total	67	32	277	26	402

This table shows the number of deals that took place between each financial sector included in the deal sample.

Table 2.6: Buyer capital by financial sector

	Uncensored (5823 obs)			Censored/deal (402 obs)		
	obs	Mean	Std Dev	obs	Mean	Std Dev
Depositary institutions	4017	18.17	8.74	67	18.22	8.44
Inv bank & other credit	494	63.42	29.12	32	48.33	29.94
Hedge fund & broker-dealers	445	85.04	14.68	277	88.54	10.98
Insurance & real estate	851	45.86	26.32	26	48.35	28.74

This table shows the average capital to assets ratios of each financial sector, for the whole sample of potential buyers and also for the sample of buyers that purchased assets.

Table 2.7: Determinants of deal probability and deal value – sectoral decomposition

Heckman selection model

	(1) probability(deal)	(2) log(deal value)
Buyer capital/assets	-0.009	0.001
	(0.007)	(0.018)
Buyer capital/assets * Inv bank & other credit	0.016**	-0.004
	(0.007)	(0.019)
Buyer capital/assets * Hedge fund & broker-dealers	0.040***	0.008
	(0.007)	(0.021)
Buyer capital/assets * Insurance & real estate	0.023***	0.015
	(0.007)	(0.019)
Buyer log(assets)	0.167***	0.516***
	(0.022)	(0.067)
Buyer log(assets) * Inv bank & other credit	0.019	0.138***
	(0.024)	(0.053)
Buyer log(assets) * Hedge fund & broker-dealers	0.005	0.221***
	(0.032)	(0.062)
Buyer log(assets) * Insurance & real estate	-0.066***	0.093
	(0.022)	(0.069)
Same city		0.213
		(0.347)
Same state		0.160
		(0.152)
Same sub-sector		0.743**
		(0.302)
US stock market return		0.007
		(0.014)
lambda		0.329
		(0.356)
Buyer asset growth	0.001	
	(0.001)	
Buyer log(market to book)	-0.163***	
	(0.063)	
Observations	5823	402

This table presents the results of estimating the Heckman selection model, including interaction terms for the financial sub-sector of the buyer. Indicator variables for the sub-sector of both the seller and buyer are included as well (not shown) and the category left out is deposit-taking banks. Other explanatory variables are as in Table 2.3.

2.6 Robustness

I perform two robustness exercises in this section. First, I estimate the selection model using the subset of deals for which the type of assets (e.g. building versus loan portfolio) was coded and control for the asset type, to ensure the results are not driven by a relationship between buyer capital and the class of assets purchased. In these 252 deals, 88 percent are properties, 7 percent are loan portfolios, and 5 percent are units or branches of banks. The results are shown in Table 2.8.

The coefficient on the buyer's capital ratio and the other explanatory variables are very close to the benchmark estimation. The dummy variables for asset type indicate that loan portfolios sell for 2.24 million more than properties, on average.

Finally, Table 2.9 shows the results of estimating equation 2.2 on the full sample of transactions involving US sellers – those bought by US firms as well as the other 15 countries listed in the data section.[10] The estimated coefficients are close to the estimates from the original OLS estimation shown in Table 2.2. The increase in value when a deal occurs between two firms in the same sector is now smaller, however, by about 1 million US dollars. In column (2), I include an interaction term for buyers that are from countries

[10] I do not estimate a selection model here because (1) identifying the universe of potential buyers is less straightforward than for the United States and (2), even having done so, the number of 'zeros' (non-purchases) in the selection equation would be problematic for the estimation. Just around 15 percent of sales from US firms had foreign buyers. A potentially fruitful future project would be to study deals between a broader set of countries.

Table 2.8: Determinants of deal value – controlling for type of asset

Heckman selection model

	(1) probability(deal)	(2) log(deal value)
Buyer capital/assets	0.036***	0.066***
	(0.002)	(0.015)
Buyer log(assets)	0.199***	0.767***
	(0.019)	(0.091)
Same city		-0.141
		(0.395)
Same state		0.456***
		(0.170)
Same sub-sector		0.993***
		(0.346)
US stock market return		-0.005
		(0.016)
Asset type: loan portfolio		0.810*
		(0.442)
Asset type: bank branch/unit		0.572
		(0.642)
lambda		1.193***
		(0.426)
Buyer asset growth	0.002	
	(0.002)	
Buyer log(market to book)	-0.127*	
	(0.074)	
Observations	5673	252

This table shows the results of estimating the two-stage model on a subsample of data for which the type of asset – be it real estate property, a loan portfolio, or a unit or branch of a bank – was coded. The category 'property assets' is left out, while indicators for 'loan portfolio' and 'bank branch/unit' are included. The variables are described in Table 2.3.

that were in financial crisis starting in 2007 or 2008, according to the classification by Laeven and Valencia (2008). This includes the United States. There does not appear to be a different effect of capital on deal value for countries in crisis. The positive effect of buyer size on deal value is larger when the buyer is from a crisis country, however.

Table 2.9: Determinants of deal value – US sales to buyers in all countries

OLS

	(1)	(2)
Buyer country in crisis		-1.956*
		(1.016)
Buyer capital/assets	0.015***	0.015***
	(0.003)	(0.003)
Buyer capital/assets * buyer country crisis		-0.007
		(0.006)
Buyer log(assets)	0.563***	0.528***
	(0.039)	(0.042)
Buyer log(assets) * buyer country crisis		0.328***
		(0.083)
Same city	0.062	0.128
	(0.291)	(0.284)
Same sub-sector	0.447**	0.443**
	(0.194)	(0.190)
(Buyer - US) stock market return	0.028	0.037
	(0.072)	(0.073)
Observations	591	591
Adj R squared	0.361	0.377

This table presents the estimation of the deal value equation using OLS, including institutions in all countries that purchased an asset from the United States. buyer country crisis' is an indicator variable for whether the buyer's country is in a financial crisis, starting in 2007/2008, according to the Laeven and Valencia (2008) classification. (Buyer – US) stock return is the difference the in the stock market return of the buying institutions' country and the US return. The other variables are as in Table 2.3.

2.7 Summary and conclusion

I study asset transactions between financial firms in the United States and find that greater capital, or lower leverage, increases the probability that a potential buyer will purchase an asset and also increases the value of the deal that takes place. This does not hold for deposit-taking institutions, however, who had greater access to or cheaper funding during the financial crisis. These results are consistent with theories that posit that demand for assets is a function of funding availability, and show that credit-constraints of financial intermediaries can interact to reduce asset prices and deepen liquidity crises. It would be interesting to see whether these results hold for assets transaction in other countries, where government policies providing support to the financial sector differed.

Chapter 3

Interconnections in Banking, Systemic Risk, and Crisis

3.1 Introduction

The recent global financial crisis has prompted a renewed interest in the factors that lead to fragility in the financial sector. Waves of panics or failures of banks have been common throughout history in both high and middle-to-low income countries (Reinhart and Rogoff 2009) and, despite an increase in the number of government policy interventions designed to stabilize the banking system, recent decades have not seen a decrease in the frequency of banking crises (Calomiris 2009). In addition to being a recurring phenomenon, banking crises are costly for the economies involved, through their role in triggering or deepening recessions and increasing the debt of governments who engage in bank bailouts.[1]

Recent policy discussions on preventing future banking crises focus on banks that are too big, or too interconnected, to fail. The idea being that the failure of large or interconnected banks has serious negative effects for non-financial sectors or contagion risks to other banks. The data on banks' exposures needed to measure interconnectedness may be reported in part to national banking regulators in some countries, but is not currently publicly available. This paper proposes a novel market-based measure of banking sector interconnectedness which can be calculated for a large group of countries – the correlation of banks' stock returns – and asks whether interconnected banking sectors are more likely to end up in crisis.

The theory on individual bank fragility is well established, traditionally focusing on the maturity mismatch between bank liabilities and assets. The creation of long-term assets from short-term deposits leaves banks susceptible to panic-based runs on their liabilities (Bryant 1980, Diamond and Dybvig 1983). A number of extensions of the Diamond-Dybvig model relate bank runs to sunspots, and Goldstein and Pauzner (2005) link the probability of a bank run to a signal about the overall state of the economy. Models that incorporate spillovers between banks, which lead a failure to, in fact, become a crisis, have been put forth more recently. Chen (1999) extends

[1] Considering 42 of the systemic banking crises that occurred between 1970 and 2007, Laeven and Valencia (2008) calculate an average fiscal cost associated with crisis management of 13.3% of GDP, and output losses (measured as deviations from trend) averaging about 20% of GDP during the first four years of crisis.

Diamond-Dybvig to a set up with multiple banks and interim revelation of information about the performance of some banks. With depositors who update according to Bayes rule, a sufficient number of interim bank failures results in pessimistic expectations about the general state of the economy and leads to runs on the remaining banks. In practice, multiple bank failures are likely to be a more precise signal to depositors about the health of the banking industry than economy-wide activity. In the model of Acharya and Yorulmazer (2008), depositors have information on the extent to which banks lend to the same risk-type of borrowers (borrowers who will invest in the same industries, for example). The information spillover from one bank failure then shows up in increased borrowing rates for remaining banks and potentially also in bank failures (if the increased rates are high enough).

I use the correlation of banks' stock returns as a proxy for interconnectedness to study the relationship between interconnectedness and banking system stability. De Nicolò and Kwast (2001) and Billio, Getmansky, Lo, and Pelizzon (2010) also use stock returns, or indexes of stock returns, to measure linkages between financial institutions. Observing that bond prices reflect individual default risk while credit default swap contracts also reflect counterparty risk, Giglio (2010) uses the information content of bond and credit default swap prices for 15 large US and European financial institutions to create bounds on the probability of joint failures. My measure of interconnectedness can be calculated from data that is readily available for banks in a large number of countries, which makes it ideal for a cross-country comparison of banking sector distress. First, I estimate a binary Logit probability model to see whether banking crises, as classified by Laeven and Valencia (2008, 2010) are more likely in interconnected banking sectors. After performing the benchmark estimation, I use an instrumental variables estimation procedure to ensure the results are not driven by endogeneity of banks' stock return correlation. Second, I estimate the relationship between interconnectedness and the number of bank failures in times of crisis, which is indicative of its severity, using an ordered Logit model. Boyd, De Nicoloò, and Loukoianova (2009) suggest that since banking crisis indicators are constructed in large part using information on government actions undertaken in response to bank distress, they do not accurately measure the start of a banking crisis but instead capture a variety of government policy responses that occur after the onset of crisis. Third, in light of these concerns about the accuracy of the crisis indicators used in the previous empirical literature, I also consider the number of bank failures that occur in each year, whether a crisis period or not. I estimate the probability of bank failures in all years, distinguishing between large banks and small banks, to see whether the relationship between interconnectedness holds in all periods and similarly for large and small banks.

For a sample of 45 countries from 1993 to 2009, I find that both the probability of a banking crisis and the probability of a greater number of large bank failures during times of crisis is increasing in banking sector interconnectedness. I also find that the probability of large bank failures is higher for more connected banking sectors in all years. No significant relationship between the interconnectedness of small banks and the probability of small bank failures is found. The paper proceeds as follows: section 3.2 reviews the related literature, section 3.3 describes the measure of interconnectedness, section 3.4 describes the data and empirical method, section 3.5 discusses the results, section 3.6 includes robustness tests, and section 3.7 concludes.

3.2 Related literature

3.2.1 Literature on banking crises

The first empirical studies of banking crises found that the probability of crisis was higher in countries with a weak prior macroeconomic environment and a weak institutional environment.[2] The literature then expanded into empirical studies of two types: (i) studies of how the economic structure of a banking sector affects its likelihood of having a crisis and (ii) an early-warning systems literature whose goal is to predict the onset of crises. The main findings from the first set of studies are that the probability of banking crisis is decreasing in the concentration or competitiveness of a banking system (Beck, Demirgüç-Kunt, and Levine 2006; Schaeck, Cihak, and Wolfe 2009,

[2]Specifically, the factors that have been found to be positively related to the likelihood of crisis are: low real GDP growth, high inflation, high real interest rates, financial liberalization, lending books, asset price declines, weak law and order, weak accounting standards, and weak legal enforcement. See Demirgüç-Kunt and Detragiache (1997, 1998), Hardy and Pazarbasioglu (1999), and Hutchison and McDill (1999).

among others) and, while most cross-country differences in banking regulation and supervision do not have significant effects, the stringency of official capital requirements decreases the probability of banking crises (Barth et al 2004).[3] Demirgüç-Kunt and Detragiache (2002) find that the existence of an explicit deposit insurance scheme increases a country's probability of having a banking crisis. The authors suggest that the positive relationship may be the result of a moral hazard effect of deposit insurance, whereby deposit-taking institutions with limited liability increase their risk-taking. The early warning systems literature is growing (see Frankel and Saravelos (2010) and chapter 3 of the IMF's September 2011 Global Financial Stability Report). Rose and Spiegel (2009), however, estimate a multiple-indicator multiple-cause model for 107 countries to examine sixty-five potential causes of the 2008 crisis and find few factors that are robustly linked to the incidence of crises across countries. They warn that this bodes poorly for early warnings models, which would have to predict the timing of crises out-of-sample in

[3]Policy studies of the overall economic effect of increasing banks' capital requirements have recently been conducted by the Basel Committee on Banking Supervision (BCBS) and economists at the Bank of Canada and the Bank of Japan. Expecting a negative relationship between capital adequacy and the likelihood of a banking crisis, these papers estimate probability of crisis models to help quantify the expected benefit of higher capital requirements. Perhaps as a result of having a very specific goal in mind, these studies each focus on a small group of countries and use few explanatory variables in their Logit or Probit probability of crisis estimations. As expected, they find that a higher capital ratio in the banking sector reduces the probability of a banking crisis. Specifically, the Bank of Canada report (August 2010) finds that an increase of 2 percentage points in the aggregate capital to assets ratio decrease the probability of a banking crises by between 0.8 and 2.6 percentage points. The BCBS/FSB Long Term Economic Impact report found that an increase of 2 percentage points in bank capital ratios reduced the probability of a financial crisis by 2.9 percentage points.

addition to successfully predicting crises in the cross-section.

Instead of relying on the standard events-based indicators of banking crises,[4] Von Hagen and Ho (2007) develop an index of money market pressure and identify banking crises as periods in which there is excessive demand for liquidity in the money market. Defining crisis episodes in this way, they find evidence for macroeconomic factors that precede banking crises that are consistent with prior studies.[5] In addition, several papers study the interplay between banking crises and currency crises or sovereign debt crises (Kaminsky and Reinhart (1999), Glick and Hutchinson (2000), Reinhart and Rogoff (2011)).

3.2.2 Measuring systemic risk

Systemic risk is the risk of joint defaults in the financial system. That is, the risk of a banking crisis occurring. De Bandt and Hartmann (2000) provide precise definitions of systemic risk and crises.[6] Banking crises result from

[4]Demirgüç-Kunt and Detragiache (2002, 2005), Caprio et al. (2005), Reinhart and Rogoff (2008b), and Laeven and Valencia (2008, 2010). These banking crisis indicators build on the classification first compiled by Caprio and Klingebiel (1996, 1999).

[5]That is, that a slowdown of real GDP, lower real interest rates, extremely high inflation, large fiscal deficits, and over-valued exchange rates tend to precede banking crises in 47 countries from 1980 to 1996.

[6]A *narrow* systemic event is one in which the release of bad news about a financial institution, or its failure, leads in a sequential fashion to considerable adverse effects on one or several other financial institutions. That is, a case where a failure of one bank due to an idiosyncratic shock spreads to another bank or several other banks. A *broad* systemic event includes not only the events described above but also simultaneous adverse effects on a large number of institutions or markets as a consequence of a severe and widespread (systematic) shock. Next, a systemic event is categorized as *strong* if the institution(s) affected in the second round or later actually fail as a consequence of the initial shock, although they were solvent ex ante. Putting these together, their definition

two types of events: (1) an idiosyncratic shock that causes one financial institution to fail, with this failure spreading to other institutions, or (2) a systematic shock that affects multiple financial institutions causing a joint default. Most crises will in fact lie in between these two extreme types but, for a given set of external shocks, banking systems in which banks are more connected, whether through similar distributions of claims on non-financial firms or significant claims on each other, will be more likely to end up in crisis. A more interconnected banking system may have a more severe crisis in response to a systematic shock. In practice, the onset of banking crises are dated based on a combination of: (i) observing a large number of defaults in a particular country, (ii) large changes in the aggregate balance-sheet of the banking sector that indicate distress,[7] and (iii) some judgment about the seriousness of the events. When identifying banking crises, of course, it is difficult to differentiate between crises that result from the propagation of an idiosyncratic shock versus crises that are due to systematic shocks.

Recent work on systemic risk focuses on measuring the individual contributions to systemic risk of particular financial institutions. Acharya, Pedersen, Philippon, and Richardson (2010) measure a financial institution's contribution to systemic risk (the systemic expected shortfall) as its propensity to be undercapitalized when the system as a whole is undercapitalized.

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of a systemic crisis is a "systemic event (narrow or broad) that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system."

[7] For example, an exhaustion of aggregate banking system capital, or sharp increases in non-performing loans.

The CoVaR measure of Adrian and Brunnermeier (2009) captures the Value-at-Risk of financial institutions conditional on other institutions being in distress. These analyses aim to measure contributions to systemic risk by conditioning on manifestations of systemic risk – that is, on financial crises – with the goal of improving the regulation and supervision of individual banks, which is currently based on individual risk measures. The goal of this paper is to use variation in the interconnectedness of banking sectors across countries to determine if greater interconnectedness in the sector increases the probability that a crisis will occur.

An analysis of systemic risk in the Unites States that is closest in spirit to my measure of interconnectedness is that of Billio, Getmansky, Lo, and Pelizzon (2010). They calculate Granger causality networks among the returns of indexes of the one-hundred largest banks, brokers, hedge funds, and insurance companies in the United States for five different sub-periods: 1994-1996, 1996-1998, 1999-2001, 2002-2004, and 2006-2008. They find that connections increase before financial crises (the crisis triggered by the collapse of Long Term Capital Management in 1998, and the subprime crisis) and during crises. Observing that bond prices reflect individual default risk while credit default swap contracts also reflect counterparty risk, Giglio (2010) uses the information content of bond and credit default swap prices for 15 large US and European financial institutions to create bounds on the probability of joint failures. My measure of interconnectedness can be calculated from data that is readily available for banks in a large number of countries, which makes it ideal for a cross-country comparison of banking sector distress and allows it to shed light on the relationship between interconnectedness before a crisis and the manifestation of crises.

3.3 Measure of interconnectedness

To measure interconnectedness in the banking sector, I calculate the correlation of the quarterly stock returns of the largest ten banks in each country, over the previous 3 years. That is, I calculate the rolling three-year (12 quarter) correlation between each pair of banks and take the simple average.[8] In the absence of data on the returns on banks' loan and securities portfolios, the correlation of stock returns serves as a proxy for the correlation of their portfolio returns. There is a positive relationship between the accounting return on assets (net income divided by assets) of banks and stock returns in all but one country in the sample. Market returns reflect information more rapidly than measures based on accounting variables and the frequency of stock price data allows us to measure the correlation more precisely than could be done using information from annual accounting data.

Two prior studies have used stock returns to measure interconnections between banks. As previously mentioned, Billio et. al. (2010) use the correlations of returns of indexes of US financial institutions to measure the linkages component of systemic risk[9] and, in a study of whether the consoli-

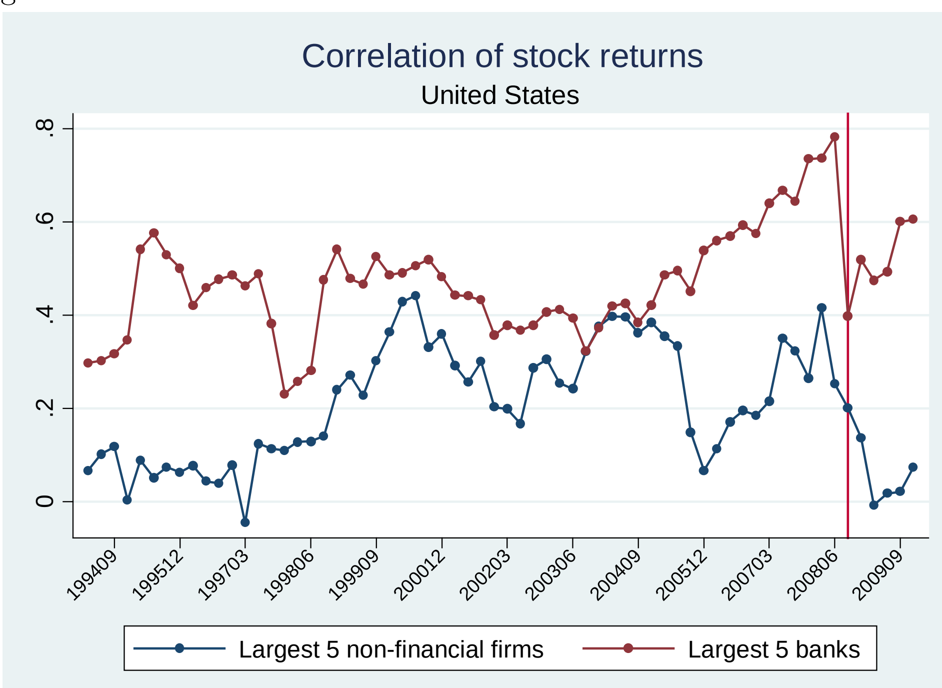
[8]The results are robust to using the correlation of the returns of the largest five banks, by assets, and also to using five-year (20 quarter) rolling windows instead.

[9]Their framework is meant to cover the"four L's" of systemic risk: liquidity, leverage,

dation of financial firms in the United States throughout the 1990s increased systemic risk, De Nicolò and Kwast (2001) use the correlation of the stock returns of large and complex banks as a measure of their interdependencies.

Figure 3.1 shows the correlation measure calculated for the largest 5 non-financial firms in the United States, and Figure 3.3 of the appendix shows the correlation measure calculated for the largest 5 firms in several different sectors in the United States. There is no comparable increase in the correlation measure prior to the crisis for the non-financial sectors.

Figure 3.1: Interconnectedness of largest 5 banks and interconnectedness of largest 5 non-financial firms in the US



linkages, and losses.

Table 3.1 shows the number of banking crises in the sample and the time in crisis as the correlation measures increases. There is a positive relationship between crises and the correlation measure: in the lowest tertile of the correlation measure, 6.6% of the sample is in a banking crisis, while in the highest tertile it increases to 22% in crisis.

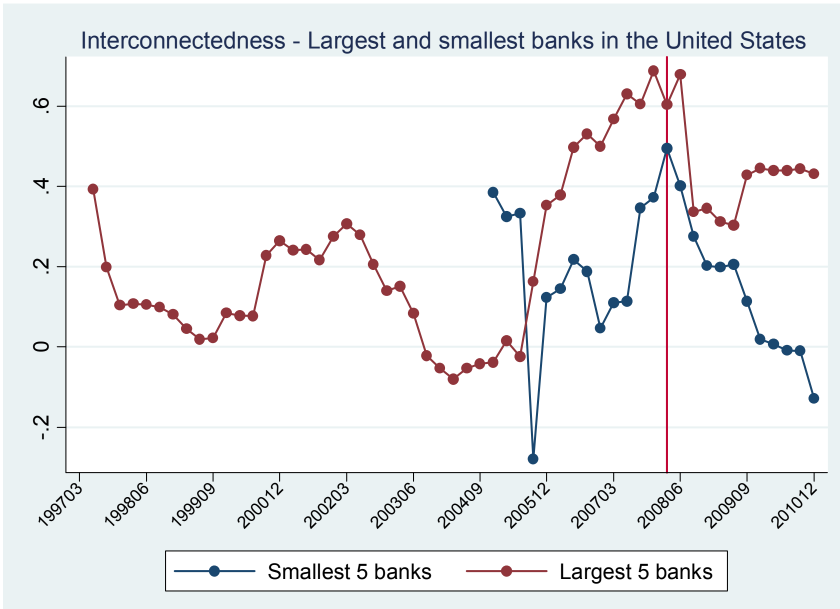
Table 3.1: Number of banking crises and time in crisis by interconnectedness

	Correlation of Bank Stock Returns (top 10)			
	Tertile 1	Tertile 2	Tertile 3	
Mean	0.072	0.590	0.904	
Crisis Years (%)	6.57	9.90	21.97	*Chi-squared: 16.4****
No. Crises	3	3	17	*Chi-squared: 18.8****

I also split the sample into the largest and smallest banks in each country and calculate the measures of interconnectedness using the correlation of the stock returns of the largest 5 banks and of the smallest 5 publicly-traded banks, respectively. Figure 3.2 shows the interconnectedness of large banks and of small banks in the United States over time. The interconnectedness of both the largest banks and smallest banks increased in the years prior to the subprime crises, but the increase was steadier for the largest 5 banks.

Several potential problems with the measure of interconnectedness must be addressed. First, do changes in the stock return correlation simply reflect changes in the overall stock market? In order to ensure this is not the case, I scale the stock price of each bank by the price of a national market index for the country in which the bank is located and calculate correlations using the

Figure 3.2: Interconnectedness of large banks and interconnectedness of small banks in the US



stock returns based on these relative prices.[10] Second, do cross-country differences in the stock return correlation reflect national factors that determine stock prices? The estimation strategy described in the next section includes country factors and the instrumental variables estimation in the robustness section shows that the main results are not driven by simultaneity.

[10] I also control for market returns and volatility in the robustness section.

3.4 Data and empirical method

3.4.1 Probability of a banking crisis

To study the relationship between banking sector interconnectedness and the probability of a crisis, I conduct a panel estimation using a Logit probability model. In the benchmark specification, an indicator variable equal to one when country i is in a banking crisis in year t is regressed on the variable of interest – the measure of interconnectedness – and control variables Z, both lagged by one year, country fixed factors α_i and year effects v_t:

$$\Pr(Y_{it} = 1) = \Lambda(\alpha_i + \beta Interconnectedness_{i,t-1} + Z_{i,t-1}\gamma_1 + v_t) \qquad (3.1)$$

where $\Lambda(\beta X) = \exp(\beta X)/\exp(1 + \beta X)$ is the logistic function. A positive and significant estimate of β indicates that banking sectors that are more interconnected are more likely to end up in crisis. I use the dates of banking crises provided by Laeven and Valencia (2008, 2010), discussed further in section 3.4.4, to create the banking crisis indicator.[11] Using this method, twenty-three crises occur between 1993 and 2009 in the 45 country sample. Table 3.11 of the appendix lists the countries and banking crises in the sample. $Interconnectedness_{i,t-1}$ is the 12 quarter (three-year) rolling correlation of the quarterly stock returns of country i's largest ten banks discussed in

[11]The majority of the previous literature on the probability of banking crises is based on these indicators of banking crises. Von Hagen and Ho (2007) is an exception.

the previous section.[12]

Turning to the control variables, as in prior studies of banking crises, real GDP growth is included to capture macroeconomic developments that may affect the quality of bank's assets. A time-variant dummy variable equal to one in the presence of an explicit deposit insurance policy and the Ilzetzki, Reinhart and Rogoff (2008) classification of the exchange rate regime, which is increasing in flexibility, are also included as controls. The share of financial sector assets that is foreign is included to control for the banks' susceptibility to foreign shocks, and the log of per capita GDP in US dollars is a proxy for differences in the institutional environments of each country. Country fixed-effects are included in all specifications, to control for any inter-country variation that is constant over the sample period. For example, one would expect variation in the strength of banking regulation and supervision across countries to affect the probability of banking crises.[13] Time dummies are included in all specifications, to capture time-dependent shocks to the world economy. All of the explanatory variables are lagged by one year to minimize concerns about possible simultaneity. In addition, as in the previous literature, I keep only the first year of a banking crisis and the years in which there

[12]The results are very similar using the three-year rolling correlations of the top five banks, by assets, as well as the five-year rolling correlations of the top 10 banks or top 5 banks.

[13]Barth, et al (2004), however, create indexes of various components of banking regulations and supervision for a cross-section of countries in 1999, and find they have little significance in explaining banking crises after including country indexes of the quality of institutions in the analysis. Also, since regulation varies little over time and, specifically, because the indexes are time-invariant, it is not possible to include both the indexes of regulation and country fixed effects in the estimation.

was no crisis in my sample to minimize concerns about possible endogeneity between the explanatory variables and the occurrence of crises. That is, the subsequent years of each banking crises are not included in the estimation.[14] Standard errors are adjusted for heteroskedasticity following Huber (1967) and White (1980), generalized to allow for correlation within countries.

3.4.2 Probability of n bank failures during a crisis

Next, I identify the number of banks that failed during each crisis and estimate the relationship between interconnectedness and the number of bank failures using an ordered Logit model. Systemic risk is defined as the risk of joint failures, but the banking crisis indicators used in the literature use a variety of data to determine whether a banking crisis has occurred. Even after the establishment of deposit insurance funds to protect depositors in the case of failures, many governments have continued to rescue distressed banks precisely due to concerns about contagion. The number of bank failures is an indication of the severity of a banking crisis, although the importance of the particular banks that failed must of course be taken into account. I distinguish between the number of large and small bank failures, where large

[14]The discrepancies across different classifications of crises are greater for the end dates than the starting dates. For example, for only the start year of the crisis, the discrepancy between the Laeven and Valencia classification and that of Reinhart and Rogoff is equal to 1.7 percent of common country-years, but when considering all crisis country-years, the discrepancy is 7 percent. So for robustness, I also drop years two and three of each banking crises, instead of each year until the end given in the Laeven and Valencia classification, following Dell' Ariccia, Detragiache, and Ragan (2008) who take the length of banking crises to be three years, and Demirgüç-Kunt et al. (2006) who find that GDP growth returns to its pre-crisis level in the fourth year of a crisis.

banks are those that have assets greater than the median bank in the sector. Ordered Logit models can be derived from an underlying latent variable model just as in the case of binary dependent variables.[15] We assume that the latent variable $y*$ is determined by

$$y*_{it} = \beta Interconnectedness_{i,t-1} + Z_{i,t-1}\gamma_1 + v_t + \epsilon_{it} \qquad (3.2)$$

where $\epsilon_{it} \sim \Lambda(\beta Interconnectedness_{i,t-1} + Z_{i,t-1}\gamma_1)$. The dependent variable is now the number of bank failures in country i in year t. Instead of considering each possible integer value of the number of bank failures, I let $y = 3$ when there are three or more bank failures. This reduces the number of threshold parameters to be estimated and does not affect the remaining parameter estimates which are used to interpret the partial effects of the explanatory variables. The explanatory variables are as in the binary Logit model of the previous section.

[15]Let $X = (Interconnectedness, Z)$ and $\theta = (\beta, \gamma_1)$ and define threshold parameters $(\alpha_1, \alpha_2, \alpha_3)$ such that: $y = 0$ if $y* \leq \alpha_1, y = 1$ if $\alpha_1 < y* \leq \alpha_2, y = 2$ if $\alpha_2 < y* \leq \alpha_3$, and $y = 3$ if $y* > \alpha_3$. Then the probabilities of one, two, or three failures are given by:

$$\begin{array}{rcl} \Pr(y = 0|X) & = & \Lambda(\alpha_1 - X\theta) \\ \Pr(y = 1|X) & = & \Lambda(\alpha_2 - X\theta) - \Lambda(\alpha_1 - X\theta) \\ \Pr(y = 2|X) & = & \Lambda(\alpha_3 - X\theta) - \Lambda(\alpha_2 - X\theta) \\ \Pr(y = 3|X) & = & 1 - \Lambda(\alpha_3 - X\theta) \end{array}$$

and the parameters $(\alpha_1, \alpha_2, \alpha_3, \theta)$ can be estimated by maximum likelihood.

3.4.3 Bank failures and share of failed assets in all years - large versus small banks

Regulators take different approaches to the rescue or resolution of large banks and small banks and the business models of the two groups vary. The literatures on banking crises and systemic risk are primarily concerned with the failure of large financial institutions, as these failures are likely to have the most severe effects – both in terms of contagion to other banks and on other sectors of the economy. The failures of even small banks can have detrimental effects on non-financial economic activity, however. Ashcraft (2003) finds that the failure of relatively small US banks in 1998 and 1992 permanently reduced local real county income by 3 percent, through a decline in bank lending.

In order to examine whether interconnectedness has the same effect on the failure of both large and small banks, I divide each country into two regions: the "large" banking sector and the "small" banking sector. The large banking sector is categorized in one of two ways. It includes (i) all banks that are larger than the median bank in each country-year, by assets, or (ii) all banks that have assets greater than 10 billion US dollars.[16] The small banking sector for each country-year consists of the remaining banks.

[16]I present the results using the median classification first, and results using the banks larger and smaller than 10 billion US dollars second. Initial considerations of systemically important financial institutions (SIFIs) defined them to be institutions with assets greater than 50 billion US dollars. These are primarily focused on banks in wealthier countries in Europe and the United States. I use a threshold of 10 billion US dollars to include large institutions in emerging markets.

This leaves us with a country-sector-year panel.

I then estimate the probability of a bank failure occurring in each country-sector-year using a Logit model, similar to before, except I include a (i) dummy variable for the large sector, (ii) the interaction between interconnectedness and the large sector, and (iii) the share of banking system assets in each country-sector-year observation to control for the relative sizes of the large and small sectors. The model is:

$$
\begin{aligned}
y*_{ijt} &= \alpha + \beta_1 Interconnectedness_{i,t-1} + \beta_2 D_j + \beta_3 (Interconnectedness_{i,t-1} \times D_j) \\
&+ \beta_4 Share_{ijt} + Z_{i,t-1}\gamma_1 + v_t + \epsilon_{ijt} \qquad (3.3)
\end{aligned}
$$

In this specification the dependent variable is (i) an indicator variable equal to one if there was a bank failure in sector j of country i in year t and (ii) the share of assets of the failed banks in sector j of country i in year t. A positive and significant β_1 indicates that interconnectedness among small banks increases the probability of small bank failures and a positive and significant β_3 indicates that interconnectedness among large banks increases the probability of large bank failures.

3.4.4 Data

I assemble an international panel of 45 high and middle income countries, over the period from 1993 to 2009. The dataset has four main components: the indicators of banking crises from Laeven and Valencia (2008, 2010), bank histories from the Bankscope database to determine bank failures, bank stock price data from Datastream to calculate the measure of banking system interconnectedness, and the control variables.

The most up-to-date classifications of banking crises are provided by Laeven and Valencia, henceforth LV, and Reinhart and Rogoff (2009), henceforth RR. In this paper, I use the classification of LV as they study a smaller set of countries and appear to have more precise dates.[17] See Table 1 of Boyd, De Nicoló, and Loukoianova (2009) for a comparison of four classifications of banking crises, including LV and RR. LV define a systemic banking crisis as a situation in which a country's corporate and financial sectors experience a large number of defaults and financial institutions and corporations face great difficulties repaying contracts on time. Using this broad definition of crisis, and combining quantitative data with some subjective assessment of the situation, they identify the starting year of systemic banking crises around the world since 1970. They define the end of a crisis as the year before two conditions hold: real GDP growth and real credit growth are positive for at least two consecutive years. In case there is growth in real GDP and real credit in the first two years of a crisis, the crisis is dated to end in the same year that it starts.

Information on bank failures in the United States is from the FDIC's Historical Statistics on Banking. Bank failures in other countries are identi-

[17]For example, LV dates the banking crisis in Japan from 1997 to 2001 while RR dates it from 1992 to 2000, RR do not count the 1988 US savings and loan crisis whereas LV do, and a few mistakes were noted in the dates RR compiled from other sources.

fied from the Bankscope dataset, which contains paragraph long histories of banks. Specifically, in the case of banks that have left the Bankscope dataset, the history identifies the year in which the bank has become inactive and a short description of the circumstances. I count banks that have been listed as bankrupt, liquidated, or had their banking licenses revoked as failed banks. In times of financial distress, mergers are often encouraged or forced by national authorities. The data does not allow me to distinguish between these "bad" mergers and voluntary mergers, so I do not count banks that have ceased to exist due to mergers as failed banks. The number of bank failures thus identified can be seen as an underestimate of distress in the banking sector. This is a contribution to the data on financial crises, as reliable data on bank failures does not exist for many countries. Tables 3.12 and 3.13 of the appendix show the number of bank failures, both large and small, and their mean size for each country in the sample.

The data on real GDP growth comes from the World Bank's World Development indicators and information on deposit insurance schemes comes from the World Bank's Deposit Insurance around the World dataset, which contains federal deposit insurance policies and characteristics for a large sample of countries since its inception in the United States in 1933.[18] The classification of exchange rate regimes is the fine classification from Ilzetzki, Reinhart

[18]The dataset ends in 2003, so I update the key variable, an indicator for whether there is an explicit deposit insurance scheme in place in a given country in a given year to the present and correct a mistake in the database regarding the years during which Argentina has had explicit deposit insurance. Almost all explicit deposit insurance schemes are mandatory, requiring all banks that collect time or savings deposits to join.

and Rogoff (2008). To maximize sample size, I use an unbalanced panel in which some country-year observations are missing. I exclude, however, countries for which there are less than six subsequent years of data available. Constraints on the availability of stock price data leave us with a sample of 45 countries, in which 23 banking crises took place, from 1993 to 2010, after excluding 1 percent of outliers on either tail of the distributions. Table 3.2 provides descriptive statistics for the explanatory variables.

Table 3.2: Descriptive statistics

	Obs	Mean	StdDev	Min	Max
Interconnectedness - top 10	678	0.50	0.23	-0.51	0.99
Interconnectedness - top 5	678	0.57	0.25	-0.67	0.99
Interconnectedness - bottom 5	500	0.46	0.27	-0.65	0.98
RealGDPgrowth	720	3.54	3.43	-10.89	18.29
Deposit Insurance	720	0.79	0.40	0	1
ExchangeRateRegime	716	7.57	4.32	1	15
ForeignAssets/Assets	720	17.63	16.13	0.27	74.53
Concentration (top 3 banks)	670	63.53	18.95	20.09	96.40
Share maj government owned	572	21.44	25.21	0	81
Market index quarterly return	516	4.69	16.24	-66.89	92.51
Market index volatility	488	11.29	7.90	0.32	51.92

3.5 Results

3.5.1 Probability of a banking crisis

The results of the benchmark estimation support the hypothesis that higher interconnectedness increases the probability of a banking crisis occurring. The measure of interconnectedness, the return correlation of the largest ten banks, has a positive and significant effect on the probability of crisis (see Table 3.3). The average marginal effect corresponding to the coefficient of 3.71 indicates that a 1 percent increase in the return correlation increases the probability of a crisis by 5.8 percentage points. This is a large effect and greater in magnitude than the effect of real GDP growth by 2 percentage points. Consistent with the previous literature, prior real GDP growth decreases the probability of crisis and the coefficients on the deposit insurance and exchange rate regime variables are negative, as expected, but not significant.

3.5.2 Probability of n bank failures during a crisis

While the probability of a banking crisis is increasing in the correlation measure, the results of the estimation of the probability of the number of bank failures indicate that higher correlation does not necessarily predict more bank failures, when all bank failures are counted. The estimated coefficient of interconnectedness on the probability of n bank failures, where n is 1, 2, or more than 3, is not significant when all bank failures are counted. When

Table 3.3: Determinants of banking crises – benchmark results

Dependent variable: Banking Crisis Indicator

Logit	Coefficient	Coefficient	eF/eX
	(1)	(2)	(2)
Interconnectedness (t-1)		3.709**	1.686
		(1.516)	
RealGDPgrowth (t-1)	-0.351*	-0.341*	-1.267
	(0.200)	(0.183)	
Deposit Insurance (t-1)	-2.708	-2.649	-1.978
	(1.797)	(1.969)	
Exchange Rate Regime (t-1)	-0.136	-0.143	-1.028
	(0.143)	(0.155)	
No. obs	612	612	
Pseudo-R2	0.51	0.52	
No. crises correctly predicted	18/23	19/23	
% crises + % non-crises correct	137.7	149.0	

The table presents panel regressions for 45 countries over the 1993–2009 period. The dependent variable is the banking crisis indicator, a discrete variable equal to 1 if there is a banking crisis in year t and zero otherwise. The independent variables are the rolling correlation of the largest 10 banks' quarterly stock returns, from year t-1 to t-4, real GDP growth, an indicator variable for the presence of an explicit deposit insurance scheme, the classification of the exchange rate regime, which is increasing in flexibility, the share of financial sector foreign assets (insignificant), and the log of per capita GDP in US dollars (insignificant), all lagged by one year. Country fixed effects and year effects are included. Standard errors (in parentheses below the coefficient estimates) are adjusted for heteroskedasticity following Huber (1967) and White (1980), generalized to allow for correlation within countries. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

restricting consideration to only large bank failures, however, the probability of the number of failures is increasing in interconnectedness. A one percent increase in the correlation results in a 1.4 percentage point increase in the probability of two large bank failures, and a 1.1 percentage point increase in the probability that three or more banks will fail (see Table 3.4).

When counting only the number of small banks failures, I find no significant relationship between interconnectedness and the number of failures. This could be because a larger share of the deposits of small banks will be insured deposits, making them less susceptible to failure through runs on deposits. Bologna (2011) finds indications that banks in the United States with a higher share of deposits above the level covered by deposit insurance[19] had a higher probability of failure between 2007 and 2009.

[19]That is, the share of deposits with denominations greater than $100,000. The FDIC insured deposits up to the amount of $100,000 at the start of the sample, although this was increased to $250,000 in 2008.

Table 3.4: Probability of n bank failures during a crisis

Dependent variable: Number of bank failures
Ordered Logit

	All banks	Large banks	Small banks
Interconnectedness	-0.703	1.902*	-1.791
	(0.668)	(1.105)	(0.834)
RealGDPgrowth	-0.106**	-0.160**	0.046
	(0.042)	(0.070)	(0.082)
No. obs	612	612	419
Pseudo-R2	0.34	0.39	0.33
d{Prob 1 failure}/e(Interconnectedness)	-0.02	0.026	-0.036
d{Prob 2 failures}/e(Interconnectedness)	-0.009	0.014	-0.012
d{Prob 3+ failures}/e(Interconnectedness)	-0.016	0.011	-0.014

The table presents panel regressions for 45 countries over the 1993–2009 period. The dependent variable is a discrete variable equal to 1 if there is one bank failure in country i in year t, equal to 2 if there are two failures in country i in year t, and equal to 3 if there are three or more bank failures. Banks are classified as large if they have assets greater than the median bank in each country-year observation. The independent variables are the rolling correlation of the largest 10 banks' quarterly stock returns (the correlation of the smallest 5 banks in the third column) from year t-1 to t-4, real GDP growth, an indicator variable for the presence of an explicit deposit insurance scheme, the classification of the exchange rate regime, which is increasing in flexibility, the share of financial sector foreign assets (insignificant), and the log of per capita GDP in US dollars (insignificant), all lagged by one year. Country fixed effects and year effects are included. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

3.5.3 Bank failures and share of failed assets in all years - large versus small banks

To further study the relationship between interconnectedness and bank failures in all years, we turn now to the country-sector-year panel, where the sector denotes either the large banks in a country's banking sector or the smaller banks. We again see a different effect of interconnectedness on large banks and on small banks. The estimated relationship between interconnectedness and the probability of large bank failures (table 3.5) is consistent with the results on banking crises. A one percent increase in the correlation measure is associated with an approximately 5 percentage point increase in the probability of large bank failures. The coefficient on the dummy variable for the large sector shows that the probability of failure of large banks is lower, by 7 percentage points when classifying large banks as those with assets greater than 10 billion US dollars.

Finally, corresponding to the bank failures in Table 3.5, Table 3.6 shows the results of the estimation of model 3.3 with the share of assets of failed banks to all banks as the dependent variable. These results are, as they should be, consistent with the results of the probabilities of failures presented in Table 3.5. Higher interconnectedness of large banks is associated with a higher share of failed assets, 0.63 percentage points higher for a one percent increase in correlation in the median classification. For the small banking sector, however, the estimated coefficient on interconnectedness is again negative but not significant. Interconnectedness has no significant effect on the probability of small bank failures, or the share of assets made up of small banks that fail.

Table 3.5: Probability of bank failures in all years – country-size-year panel

Dependent variable: Bank failure indicator

Logit

	Median classification		10B US$ classification	
	Coefficient	dF/eX	Coefficient	dF/eX
Interconnectedness (t-1)	-2.602***	-0.074	-2.022*	-0.034
	(0.972)		(1.124)	
Large	-3.241*	-0.126	-4.840***	-0.073
	(1.697)		(1.554)	
Large*Interconnectedness (t-1)	2.892**	0.065	5.472**	0.054
	(1.410)		(2.406)	
RealGDPgrowth (t-1)	-0.095	-0.012	-0.102	-0.008
	(0.089)		(0.121)	
Share sector (t-1)	0.028	0.106	0.006	0.010
	(0.018)		(0.004)	
No. obs	982		982	
Pseudo-R2	0.42		0.47	
No. failure cases correctly predicted	42/99		18/56	
% crises + % non-crises correct	140.4		131.2	

The table presents panel regressions for 45 countries over the 1993–2009 period. The dependent variable is a discrete variable equal to 1 if there are bank failure(s) in country i in the large or small section of the financial sector j in year t. The independent variables are the rolling correlation of banks' quarterly stock returns from year t-1 to t-4, real GDP growth, and the share of financial sector assets made up of banks in group j, all lagged by one year. Country fixed effects and year effects are included. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

Table 3.6: Assets of failed banks in all years – country-size-year panel

Dependent variable: Log share of failed assets
Logit

	Median classification		10B US$ classification	
	OLS	Tobit	OLS	Tobit
log Interconnectedness	-0.240	-0.573*	-0.339	-0.755**
	(0.210)	(0.341)	(0.203)	(0.303)
Large	0.281	-0.899	0.155	-1.338
	(0.603)	(1.131)	(0.285)	(0.864)
log Large*Interconnectedness	0.630**	1.746*	0.473*	1.035
	(0.303)	(1.033)	(0.260)	(1.194)
RealGDPgrowth	0.068*	-0.027	0.045	-0.041
	(0.038)	(0.068)	(0.038)	(0.070)
log Share sector	-0.120	0.052	-0.213**	-0.464***
	(0.141)	(0.208)	(0.101)	(0.177)
No. obs	303	303	311	311
R2	0.38		0.37	
Pseudo R2		0.14		0.20

The table presents panel regressions for 26 countries over the 1995–2009 period. The dependent variable is log (assets of failed banks in ijt/total assets in ijt). The independent variables are the rolling correlation of banks' quarterly stock returns from year t-1 to t-4, real GDP growth, and the share of financial sector assets made up of banks in group j, all lagged by one year. Country fixed effects and year effects are included. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

3.6 Robustness

3.6.1 Instrumental variables estimation

The results of the previous section indicate that the probability of a banking crisis, and similarly of the failure of large banks, is increasing in the level of interconnectedness of the banks prior to crisis. In order to ensure the results are not driven by increasing correlation in times of crises, or by factors that increase both the correlation of banks' stock returns and the probability of crises, I conduct instrumental variables estimation. The instrument for the banks' stock return correlation is the ratio of the value of total shares traded on the national stock market to real market capitalization. Although stock market capitalization is known to fall during most banking crises, there is no clear relationship expected between crises and the total value of shares traded. While the value of certain stocks may fall, turnover may increase. At the same time, increased turnover is likely to have a positive effect on the return correlation. Panel B of Table 3.7 shows the first stage regression, where the t-test that the instrument is not related to interconnectedness can be rejected at a 5% level of confidence. Panel A shows the second stage results. The 2SLS result corresponds to a linear probability model, with the standard errors corrected for heteroskedasticity, and the second stage Logit coefficient is consistent with the benchmark results. Both show that an increase in interconnectedness increases the probability of a banking crisis.

Table 3.7: Determinants of banking crises – IV estimation

Panel A:	Probability of Crisis		
	Dependent variable: Banking Crisis Indicator		
		(1)	(2)
		2SLS	2nd-stage logit
	Interconnectedness (t-1)	1.518**	37.958*
		(0.741)	(22.024)
	RealGDPgrowth (t-1)	0.008	-0.863
		(0.009)	(1.374)
	No. obs	572	572
	R2	0.22	
	Pseudo-R2		0.78
Panel B:	First Stage Estimation		
	Dependent variable: Interconnectedness		
		(1)	
	StockMarketValueTraded	0.053**	
		(0.021)	
	No. obs	572	
	F-stat	20.25	
	R-squared	0.57	

The table presents instrumental variables estimation results for 45 countries over the 1993–2009 period. Panel B present the first stage estimation, where the dependent variable is the rolling correlation of banks' quarterly stock returns and the instrument is the total value of shares traded in the stock market for country i. Panel A presents the second stage estimations, using both 2SLS (corresponding to a linear probability model) and a Logit probability model. The dependent variable is a discrete variable equal to 1 if there are bank failure(s) in country i in the large or small section of the financial sector j in year t. The independent variables are the (instrumented) rolling correlation of banks' quarterly stock returns from year t-1 to t-4, real GDP growth, an indicator variable for the presence of an explicit deposit insurance scheme, the classification of the exchange rate regime, which is increasing in flexibility, the share of financial sector foreign assets (insignificant), and the log of per capita GDP in US dollars (insignificant), all lagged by one year. Country fixed effects and year effects are included. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

3.6.2 Additional controls

To check for the possibility that the observed relationship between banking crises and interconnectedness is driven by stock market movements that affect the stock return correlation, I next control for the return on a national stock market index, as well as the volatility of the index. The positive effect of interconnectedness on the probability of banking crisis is robust to these inclusions (Table 3.8).

Past studies have found mixed results concerning the effect of competition on banking crises. I find concentration, measured as the share of assets held by the three largest banks, to have no significant effect on the probability of banking crises (Table 3.9). Karolyi and Taboada (2010) calculate the share of banks that is majority owned by the government for 1995, 2000, and 2005. In a reduced sample[20] with these three years, I check whether the share of banks that are majority government owned decreases the probability of crises, as would be expected. I find no significant effect of government ownership on the probability of crisis.

[20]The sample is reduced as the share of government ownership is calculated only for 1995, 2000, and 2005.

Table 3.8: Determinants of banking crises – overall stock market movements

Dependent variable: Banking Crisis Indicator

Logit

	(1)	(2)
Interconnectedness (t-1)	5.258**	8.410**
	(2.306)	(4.194)
Market index return (t-1)	-0.008	
	(0.023)	
Market index volatility (t-1)		0.076
		(0.074)
RealGDPgrowth (t-1)	-0.427*	-0.950***
	(0.219)	(0.315)
Deposit Insurance (t-1)		
Foreign asset share (t-1)	0.034	0.254***
	(0.065)	(0.091)
No. obs	488	465
Pseudo-R2	0.57	0.71
No. crises correctly predicted	14/20	12/20
% crises + % non-crises correct	155.2	179.5

The table presents panel regressions for 45 countries over the 1995–2009 period. The dependent variable is the banking crisis indicator, a discrete variable that equals one if there is a banking crisis in year t and zero otherwise. The independent variables are the rolling correlation of the largest 10 banks' stock returns, from t-1 to t-4, the return on a national market index in the last quarter of the prior year, the rolling standard deviation of the market quarterly returns, from t-1 to t-4, real GDP growth, an indicator variable for the presence of an explicit deposit insurance scheme, the classification of the exchange rate regime, which is increasing in flexibility, the share of financial sector foreign assets (insignificant), and the log of per capita GDP in US dollars (insignificant), all lagged by one year. Country fixed effects and year effects are included. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

Table 3.9: Determinants of banking crises – concentration and government ownership of banks

Dependent variable: Banking Crisis Indicator
Logit

	(1)	(2)
Interconnectedness (t-1)	4.633***	4.378*
	(1.662)	(2.493)
Concentration (t-1)	-0.019	
	(0.038)	
Share of Government		0.024
Owned Banks (t-1)		(0.022)
RealGDPgrowth (t-1)	-0.365**	-0.482
	(0.186)	(0.339)
No. obs	609	119
Pseudo-R2	0.55	0.18
No. crises correctly predicted	19/23	0/3
% crises + % non-crises correct	149.0	100.0

The table presents panel regressions for 45 countries over the 1993–2009 period in column (1) and for 1993, 2000, and 2005 in column (2). The dependent variable is the banking crisis indicator, a discrete variable that equals one if there is a banking crisis in year t and zero otherwise. The independent variables are the rolling correlation of the largest 10 banks' stock returns, from t-1 to t-4, the concentration of the banking sector (measured as the share of assets in the largest three banks), the share of banks that are majority government owned from Karolyi and Taboada (2010), real GDP growth, an indicator variable for the presence of an explicit deposit insurance scheme, the classification of the exchange rate regime, which is increasing in flexibility, the share of financial sector foreign assets (insignificant), and the log of per capita GDP in US dollars (insignificant), all lagged by one year. Country fixed effects and year effects are included. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

Following Allen, et al. (2002), several measures of balance-sheet risk exposure were investigated but not found to have a significant effect on the probability of banking crises. They lay out a framework for understanding crises based on the examination of stock variables in the aggregate balance-sheet of a country and the balance-sheets of its main sectors. Four types of balance-sheet mismatches help to determine a country's ability to service debt in the face of shocks: (i) *maturity mismatches*, where a gap between liabilities due in the short term and liquid assets leaves a sector unable to honor its contractual commitments if the market declines to roll over debt,[21] or creates exposure to the risk that interest rates will rise; (ii) *currency mismatches*, where a change in the exchange rate leads to a capital loss; (iii) *capital structure problems*, where a heavy reliance on debt rather than equity financing leaves a firm or bank less able to weather revenue shocks; and (iv)*solvency problems*, where assets are insufficient to cover liabilities. They note that maturity mismatches, currency mismatches, and a poor capital structure can all contribute to solvency risk, but solvency risk can also arise from simply borrowing too much or from investing in low-yielding assets.

The currency composition of bank's assets and liabilities is unfortunately not available in the Worldscope database, so currency mismatches cannot be measured. The specific measures used to address the other three risks men-

[21]The classic model of Diamond and Dybvig (1983) shows how this maturity mismatch makes banks susceptible to panic-based runs by depositors. The idea, of course, extends to other debtors of banks. Gorton (2009) illustrates how the recent financial crisis started as a run in repurchase markets (short term, or overnight, lending between financial firms).

tioned above are created as follows. First, the aggregate maturity mismatch is the ratio of the total short-term and current portion of long-term debt in the banking sector to the total value of liquid assets. The current portion of long-term debt is that which is due within a year, and liquid assets are composed of cash and investments in government securities. Exposure to risk is increasing in this measure. Second, capital structure problems are measured simply as the ratio of total capital to total assets. Exposure to risk is decreasing in this measure as capital is widely the main buffer between banks and failure, and capital adequacy is the key target of banking supervisors and regulators. Estrella et al (2000) find that capital ratios are a good predictor of bank failure in the United States from 1998 to 1992 and that, somewhat surprisingly, a risk-weighted ratio does not consistently outperform the simpler ratios, particularly with short horizons. Third, solvency risk exposure is calculated as the net worth (assets plus capital minus liabilities) of the banking sector, scaled by assets.

Table 3.10: Determinants of banking crises – balance-sheet risk exposures

Dependent variable: Banking Crisis Indicator
Logit

	(1)	(2)	(3)
Interconnectedness (t-1)	4.597**	4.643**	4.679**
	(1.962)	(2.097)	(1.974)
MaturityMismatch (t-1)	0.008		
	(0.008)		
Capital/Assets (t-1)		-0.172	
		(0.108)	-0.087
NetWorth/Assets (t-1)			(0.106)
	-0.641***	-0.358**	-0.709***
RealGDPgrowth (t-1)	(0.196)	(0.150)	(0.246)
No. obs	570	534	571
Pseudo-R2	0.60	0.55	0.60
% crises + % non-crises correct	155.9	162.3	156.1

The table presents panel regressions for 43 countries over the 1994–2009 period. The dependent variable is the banking crisis indicator, a discrete variable that equals one if there is a banking crisis in year t and zero otherwise. The independent variables are the rolling correlation of the largest 10 banks' stock returns, from t-1 to t-4, the asset-weighted mean ratio of short-term and current portion of long-term debt to liquid assets at public banks, the asset-weighted mean capital to assets ratios of public banks, the asset-weighted mean ratio of the net worth to assets of public banks, real GDP growth, an indicator variable for the presence of an explicit deposit insurance scheme, the classification of the exchange rate regime, which is increasing in flexibility, the share of financial sector foreign assets (insignificant), and the log of per capita GDP in US dollars (insignificant), all lagged by one year. Country fixed effects and year effects are included. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

3.7 Conclusion

I study the effect of interconnectedness among banks within a banking sector on banking system stability and find that (i) the probability of a banking crisis is increasing in interconnectedness, (ii) the probability of a greater number of large bank failures during crisis periods is increasing in interconnectedness, and (iii) the probability of one or more large bank failures is higher when banks are more interconnected, in all years. I interpret these results as indicative of contagion within banking sectors. When banks are more connected, the failure of one bank has adverse affect on other banks, resulting in subsequent bank failures. Interestingly, I find no significant relationship between the interconnectedness of smaller banks and the probability of small bank failures. This could be due to the fact that a larger share of the deposits of small banks are insured, making them less susceptible to failure through runs on deposits.

This paper adds to the growing literature that suggests that banking regulators could gain from incorporating stock price information into their assessments of bank risk. The focus of the paper is on linkages within banking sectors and the potential for contagion within a country. Future research on the transmission mechanisms through which financial crises spillover to other countries would be valuable.

3.8 Appendix

Figure 3.3: Interconnectedness of largest 5 firms by sector – United States

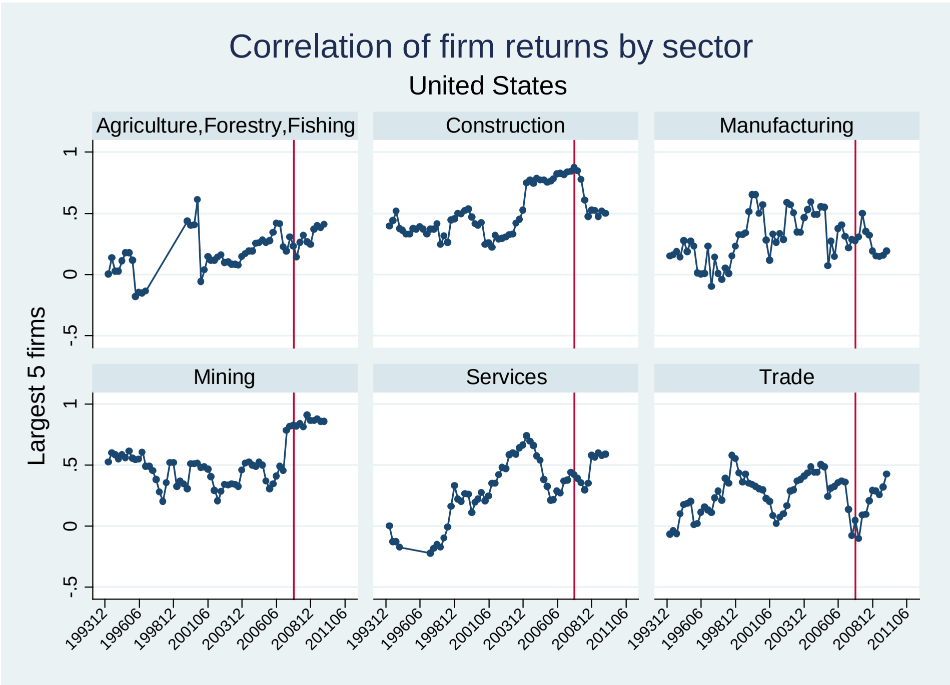


Table 3.11: Banking crises 1993-2009

Emerging and developing economies

Country	Crisis years	Non-crisis countries	
Argentina	2001-2003	Bangladesh	Pakistan
Brazil	1994-1998	Chile	Peru
Colombia	1998-2000	China	South Africa
Ecuador	1998-2002	Egypt	SriLanka
Malaysia	1997-1999	Kenya	Venezuela
Philippines	1997-2001	Lebanon	
Thailand	1997-2000	Mexico	
Turkey	2000-2001	Morocco	

Advanced Economies

Country	Crisis years	Non-crisis countries
Austria	2008-	Australia
Belgium	2008-	Canada
Denmark	2008-	Finland
France	2008-	Hong Kong
Germany	2008-	Israel
Greece	2008-	Italy
Ireland	2008-	Norway
Japan	1997-2001	Poland
Korea (South)	1997-1998	Singapore
Netherlands	2008-	
Spain	2008-	
Sweden	2008-	
Switzerland	2008-	
United Kingdom	2007-	
United States	2007-	

Table 3.12: Bank failures by country and size – median classification

Country	Total failures	Small banks Number	Small banks Mean size (millions US$)	Large banks Number	Large banks Mean size (millions US$)
Argentina	27	27	390	0	
Australia	10	1	280	3	5,403
Austria	9	7	195	2	30,489
Bangladesh	0	0		0	
Belgium	15	15	313	0	
Brazil	21	12	53	9	1,042
Canada	9	9	102	0	
Chile	0	0		0	
China	0	0		0	
Colombia	16	14	167	2	2,734
Denmark	3	0		3	517
Ecuador	3	2	64	1	863
Egypt	0	0		0	
Finland	0	0		0	
France	38	32	183	6	2,824
Germany	31	14	129	17	1,054
Greece	0	0		0	
HongKong	10	10	612	0	
India	0	0		0	
Ireland	9	3	2,093	1	11,608
Israel	3	1	65	0	
Italy	14	14	136	0	
Japan	14	5	1,434	9	22,253
Kenya	4	4	37	0	
Korea	12	0		12	2,954
Malaysia	3	2	206	1	30,044
Mexico	3	2	241	1	3,466
Morocco	0	0		0	
Netherlands	10	10	925	0	
Norway	1	0		1	3,270
Pakistan	1	1	28	0	
Peru	5	4	90	1	279
Philippines	1	1	331	0	
Poland	2	2	227	0	
Singapore	7	0		0	
SouthAfrica	13	11	309	2	2,429
Spain	4	4	504	0	
SriLanka	0	0		0	
Sweden	1	1	3	0	
Switzerland	33	28	138	5	15,566
Thailand	3	0		3	1,832
Turkey	2	2	1,052	0	
UK	37	20	320	17	9,805
USA	288	175	85	126	29,954
Venezuela	1	0		1	1,128

Large banks are those with assets greater than the median bank in each country-year.

Table 3.13: Bank failures by country and size – 10B US$ classification

Country	Total failures	Small banks Number	Mean size (millions US$)	Large banks No.	Mean size
Argentina	27	27	390	0	
Australia	10	9	1,369	1	13,787
Austria	9	7	195	2	30,489
Bangladesh	0	0		0	
Belgium	15	15	313	0	
Brazil	21	21	477	0	
Canada	9	9	102	0	
Chile	0	0		0	
China	0	0		0	
Colombia	16	16	488	0	
Denmark	3	3	517	0	
Ecuador	3	3	330	0	
Egypt	0	0		0	
Finland	0	0		0	
France	38	37	308	1	11,410
Germany	31	31	636	0	
Greece	0	0		0	
HongKong	10	10	612	0	
India	0	0		0	
Ireland	9	8	1,592	1	11,608
Israel	3	3	1,023	0	
Italy	14	14	136	0	
Japan	14	8	2,896	6	30,714
Kenya	4	4	37	0	
Korea	12	12	2,954	0	
Malaysia	3	2	206	1	30,044
Mexico	3	3	1,316	0	
Morocco	0	0		0	
Netherlands	10	10	925	0	
Norway	1	1	3,270	0	
Pakistan	1	1	28	0	
Peru	5	5	128	0	
Philippines	1	1	331	0	
Poland	2	2	227	0	
Singapore	7	7	529	0	
SouthAfrica	13	13	635	0	
Spain	4	4	504	0	
SriLanka	0	0		0	
Sweden	1	1	3	0	
Switzerland	33	31	207	2	37,641
Thailand	3	3	1,832	0	
Turkey	2	2	1,052	0	
UK	37	32	1,055	5	27,868
USA	288	280	502	8	53,108
Venezuela	1	1	1,128	0	

Large banks are those with assets greater than 10 billion US$.

Chapter 4

How Risky are Banks' Risk-Weighted Assets? Evidence from the Financial Crisis

"The leverage ratio - a simple ratio of capital to balance-sheet assets - and the more complex risk-based requirements work well together. The leverage requirement provides a baseline level of capital to protect the safety net, while the risk-based requirement can capture additional risks that are not covered by the leverage framework. The more advanced and complex the models become, the greater the need for such a baseline. The leverage ratio ensures that a capital backstop remains even if model errors or other miscalculations

impair the reliability of risk-based capital. This is a crucial consideration - particularly as we work through the implementation of Basel II standard. By restraining balance-sheet growth, the leverage ratio promotes stability and resilience during difficult economic periods."

- Remarks by Sheila Bair, Chairman, Federal Deposit Insurance Corporation before the Basel Committee on Banking Supervision, Merida, Mexico, October 4, 2006.

4.1 Introduction

The financial crisis that begain in 2007 has exposed a number of weaknesses in banking regulation. Capital requirements are the primary tool of bank capital regulation, making how to appropriately determine the riskiness of bank's portfolios a key challenge for banks, regulators, and investors. Risk-weighted assets (RWA) are an important element of risk-based capital ratios as banks can increase their capital adequacy ratios in two ways: (i) by increasing the amount of regulatory capital held, which boosts the numerator of the ratio, or (ii) by decreasing risk-weighted assets, which is the denominator of the regulatory ratio. The principle that regulatory capital requirements should be tied to the risks taken by banks was accepted internationally and formalized with the Basel I accord in 1988, and the definition of acceptable forms of capital and guidelines for measuring risk have undergone several revisions since that time. The second Basel accord, published in 2004, recommended that banks hold total regulatory capital equal to at least 8 percent of their risk-weighted assets. The recently updated Basel III guidelines recommend increasing the amount of capital that should be held and emphasize higher quality forms of capital, but continue the approach of calculating capital requirements relative to their risk-weighted assets.[1] Basel III also proposes a non-risk-weighted leverage ratio as a complementary measure.[2]

A key concern about current methods of calculating risk-weighted assets is that they leave room for individual banks to "optimize" capital requirements by underestimating their risks and thus being permitted to hold lower capital. Jones (2000) discusses techniques banks can use to engage in regulatory capital arbitrage and provides evidence on the magnitude of these activities in the Unites States. Merton (1995) provides an example in which, in place of a portfolio of mortgages, a bank can hold the economic equivalent of that portfolio at a risk-weight one-eighth as large. Innovations in financial products since the first Basel accord have also likely made it easier for financial institutions to manipulate their regulatory risk measure. Acharya, Schnabl, and Suarez (forthcoming) analyze asset-backed commercial paper and find evidence suggesting that banks used this form of securitization to concentrate, rather than disperse, financial risks in the banking sector while reducing bank capital requirements. In addition to concerns about underestimating

[1] Basel III capital standards require minimum common equity, Tier 1 capital, and total capital equal to 4.5, 6, and 8 percent of risk-weighted assets, respectively. In addition, the standards recommend an additional capital conservation buffer of 2.5 percent of risk-weighted assets. Supervisors can add a countercyclical buffer in the range of 0-2.5 percent.

[2] The specific definition and enforcement of the leverage ratio under Basel III is pending.

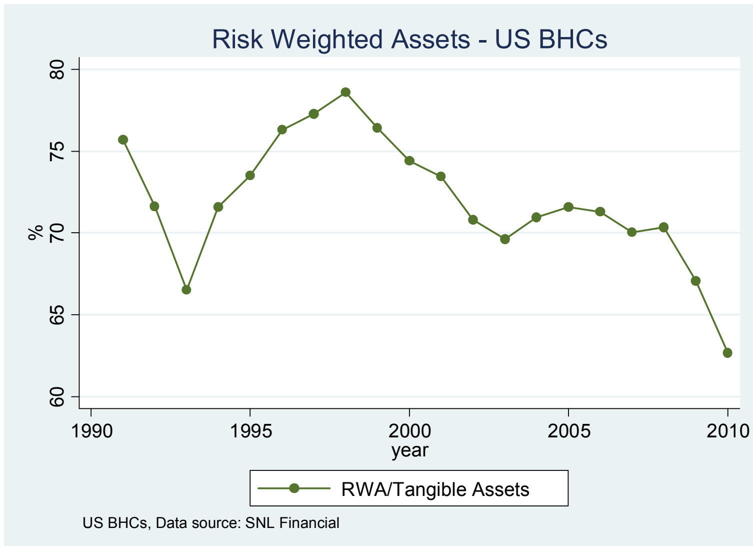
the riskiness of assets, there are differences in calculation of risk-weighted assets across countries that may have unintended effects on financial stability. Lord Adair Turner, chairman of the UK Financial Services Authority, warned last June that international differences in the calculation of risk-weighted assets could undermine Basel III[3] and Sheila Bair, former chairman of the US Federal Deposit Insurance Corporation, added her concern that Europe and the US may be diverging in their calculation of their risk-weighted assets: "The risk weightings are highly variable in Europe and have led to continuing declines in capital levels, even in the recession. There's pretty strong evidence that the RWA calculation isn't working as it's supposed to."[4]

In this paper, we ask whether equity investors find banks' reported risk-weighted assets to be a credible measure of risk. First, did banks with lower risk-weighted assets have higher stock returns during the recent financial crisis? Second, do measures of risk based on equity market information correspond to risk-weighted assets? Demirguç-Kunt, Detragiache, and Merrouche (2010) and Beltratti and Stulz (forthcoming) also study banks' stock return performance during the financial crisis, focusing primarily on the effect of different measures of capital and bank governance, respectively. Our paper studies whether markets price bank risk as measured by RWA, to inform the debate on how best to measure the risks embedded in banks' portfolios.

[3]Risk Magazine, June 24, 2011, "FSA's Turner: RWA divergence would undermine Basel III" www.risk.net/risk-magazine/news/2081533/fsas-turner-rwa-divergence-undermine-basel-iii

[4]Risk Magazine, June 24, 2011, "Europe lax on RWA calculations, says Bair" www.risk.net/risk-magazine/news/2081139/europe-lax-rwa-calculations-bair

Figure 4.1: Decrease in risk-weighted assets at US BHCs



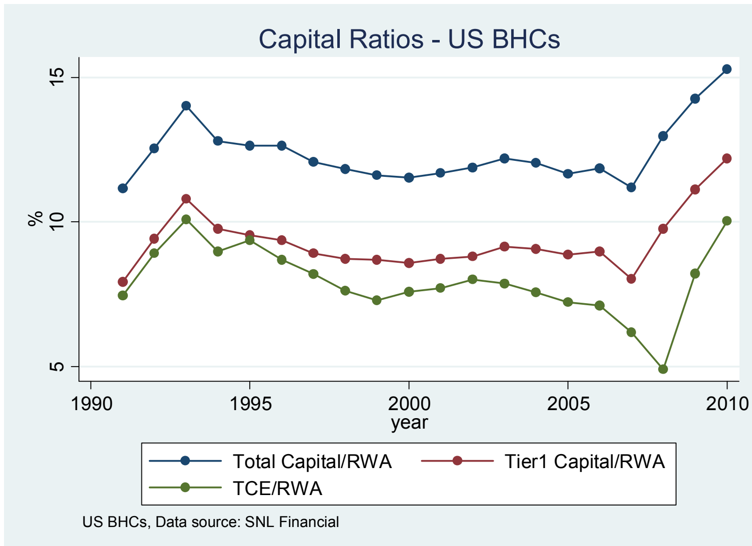
The ratio of aggregate risk-weighted assets to tangible assets at all bank holding companies (BHC) in the United States. The tangible assets of a bank are equal to total assets minus intangibles and goodwill.

4.2 Stylized facts

The past decade has seen a decrease in the measured risk-weighted assets of banks, as well as a decrease in the quality of capital held by banks. For instance, there is a downward trend in the aggregate ratio of risk-weighted assets to tangible assets for US bank holding companies since the late 1990s, shown in Figure 4.1.

Figure 4.2 shows the downward trend in three measures of capital as a percentage of risk-weighted assets at bank holding companies in the United States in the years preceding the crisis. This decline is sharpest in tangible common equity, which has the greatest loss-absorbing capacity, and less

Figure 4.2: Quality of regulatory capital at US BHCs

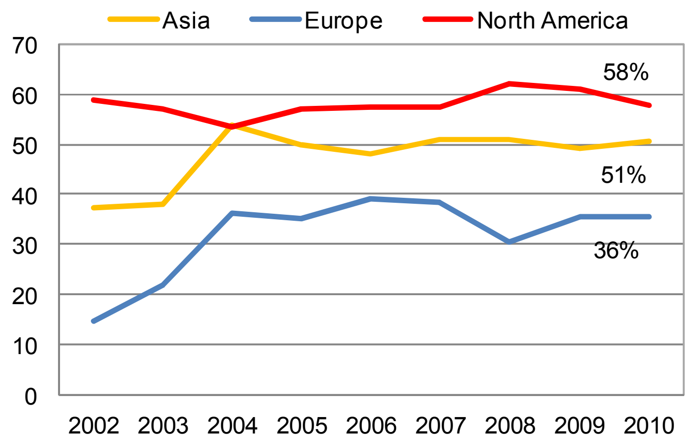


Tangible common equity (TCE) is equal to common equity minus intangibles and goodwill. Tier 1 capital includes shareholders equity, both common equity and non-cumulative preferred stock, and retained earnings. Tier 2 capital includes subordinated debt, hybrid instruments - such as perpetual preferred stock, revaluation reserves, general provisions, and undisclosed reserved are also permitted by regulators in some countries. Total capital is the sum of Tier 1 capital and Tier 2 capital.

pronounced in total regulatory capital.

There are also differences in RWA between geographical regions. On average, European banks have much lower RWA as a share of their total assets than banks in North America or Asia (see Figure 4.3).

Figure 4.3: Ratio of RWA to total assets in Asia, Europe and North America (2002-2010)



Source: Bloomberg, SNL Financial. Aggregate ratios of RWA to total assets for banks in Asia, Europe, and North America. Data are for a sample of the largest banks in each region.

4.3 Risk-weighted assets: Basel II Standardized and IRB Approaches

The 1998 Basel I Accord proposed a simple framework for measuring risk based on risk buckets' for four broad categories of claims: sovereigns, banks, mortgages, and corporate. In contrast, Basel II aimed at improving the risk sensitivity of capital requirements. A prelude to the Basel II internal ratings-based (IRB) approach was the adoption by the Basel Committee in 1996 of the value-at-risk (VaR) approach to determine capital requirements for market risk (subsequently integrated into the Basel II framework). The 2004 Basel II accord extended a similar approach to credit risk. It opened the way for banks to determine risk-weights using external credit rating agencies or their own internal ratings systems based on historical default data, after supervisory validation, and to calculate the parameters of a uniform regulatory formula.

For banks not (yet) deemed by supervisors to be able to implement model-based approaches, Basel II contemplated simplified approaches for each of the risk categories it covered. In particular, the Standardized Approach (SA) for credit risk provided a much more differentiated treatment of exposures than Basel I, while allowing risk-weights for each exposure to vary according to ratings issued by external credit rating agencies. However, although external ratings could drive risk weights significantly higher than Basel I's highest weight of 100 percent, they could also drive them much lower. Moreover, in the important case of home mortgage loans, the risk weight was reduced from 50 to 35 percent.

The Basel II IRB approach is built on three risk parameters: (i) the probability of default (PD), which describes the likelihood that an obligor will default, (ii) the exposure at default (EAD), and (iii) the loss given default (LGD), which describes the loss rate on the exposure in the event of default.[5] Indeed, the level of regulatory capital that a bank should hold depends on the amount of loss it is expected to exceed with a small, pre-defined probability – the Value-at-Risk (VaR). Capital is set according to the

[5]The Basel II IRB formula is based on an asymptotic single-risk factor (ASRF) model. See Basel Committee on Banking Supervision (2005).

bank's unexpected loss (UL) which is the gap between the bank's expected loss (EL) and Value-at-Risk at a certain confidence level, over a one-year horizon. The expected loss is calculated as follows:
$EL = PD \times EAD \times LGD$ or, in percentage of $EAD, EL\% = PD \times LGD$.

The supervisory capital charge as a percentage of the exposure (K) is set using a Merton model which depends on PD and LGD. Risk-weighted assets (RWA) are then expressed as a function of the capital requirement and the minimum capital ratio of 8 percent (or its reciprocal 12.5):

$$RWA = 12.5 \times K \times EAD.$$

It is important to note that under the Basel II IRB approaches, banks have considerable discretion in reporting their own average PD, and also EAD and LGD under the advanced IRB.

Basel III improves risk weights on exposures to market risk but leaves Basel II standardized approach (SA) risk weights on credit risk exposures unchanged. However, banks are now expected to use higher than external-ratings-based risk weights if their own risk assessment so warrants.

4.4 Related literature

This study expands on two main strands of literature. First, this paper is related to studies of bank resilience during the recent financial crisis. Demirguç-Kunt, Detragiache, and Merrouche (2010) find that capital was positively related to banks' stock returns during the crisis[6] and Beltratti and Stulz (forthcoming) find that large banks with more capital[7] and higher reliance on deposits for short-term funding in 2006 had higher stock returns during the crisis, but these factors did not have a robust impact on bank risk, as measured by the bank's idiosyncratic volatility and distance-to-default. In earlier works, Kim and Santomero (1988) use a mean-variance model to evaluate the effectiveness of both a uniform capital ratio requirement and a risk-related capital plan in controlling bank risk and derive theoretically correct risk-weights to maintain banking system soundness, and Berger, Herring and Szego (1995) discuss the difficulty of developing an accurate measure of risk exposure that is reasonably simple and can be uniformly applied across banks.

Second, we build on the empirical literature that studies bank risk-taking and regulatory risk in the United States. Avery and Berger (1991b) and Bradley et al (1991) find that RWA for banks and for thrifts, respectively, are positively related to the bank or thrift's probability of failure and accounting measures of risk, but that these relationships are fairly weak. Cordell and King (1995) compare stock market measures of risk to regulatory risk-based capital measures for banks and thrifts in the United States in 1990. Their

[6]Specifically, they find that during the crisis, a stronger capital position was associated with better stock market performance, most markedly for larger banks, and the relationship between stock returns and capital is stronger when capital is measured by the leverage ratio (capital to total assets) rather than the risk-adjusted capital ratio.

[7]They test both the ratio of Tier1 capital to RWA and tangible equity to total assets. The regulatory ratio is found to be statistically significant in most regression specifications.

results suggest that market and risk-based capital standards agree to some extent on the adequacy of institutions' current capital, but the measures of asset risk are not positively correlated.

Most importantly, we shed light on the credibility of RWA as currently measured. The debate on the appropriate capital requirements for banks has reached consensus on higher capital requirements, but the discussion of appropriate measurement of asset-risk has come to the forefront only recently. Acharya (2011) notes that the importance of residential housing as an asset class increased endogenously in response to the low risk weights on residential mortgage backed securities in capital requirements and, although the subprime crisis showed that banks were clearly not holding enough capital against these assets, the relatively low risk weight on this asset class has continued. The significance of the problem is also clear in the current Eurozone sovereign debt crisis. The zero risk weights on European banks' holdings of the debt of their sovereigns are clearly not in line with current assessments of their riskiness.

In studying the effects of government bailouts, Duchin and Ross (2012) find evidence that bailed-out banks approve riskier loans and shift investment portfolios toward riskier securities. This shift in risk occurs mostly within the same asset class and therefore has little effect on the closely monitored capitalization levels. Consequently, bailed-out banks appear safer according to the capitalization requirements, but show a significant increase in market-based measures of risk. They conclude that those banks' responses to capital requirements may erode their efficacy in risk regulation.

To what extent are differences between regulatory and market assessments of risk problematic? Market discipline requires investors to both (i) monitor the condition of banks and incorporate those assessments into their stock prices, and (ii) influence the managers of banks through these changes in stock prices (Bliss and Flannery 2001). This study does not delve into whether market participants are able to influence banks managers but instead focuses on the first, necessary, component of discipline. That is, how does the market assess the riskiness of banks based on their regulatory reports, balance-sheet, and income statements? Even if markets are not able to influence manager's actions,[8] an understanding of their assessments is important in that bank regulators and supervisors can incorporate this information into their assessments and actions.

4.5 Data and Methodology

The sample consists of 804 publicly-listed deposit-taking institutions[9] in 32 countries, spanning North America, Europe, Asia, and Australia. These are listed in Table 4.12 of the appendix. The balance-sheet and income statement

[8]There is some support for market influence in banking. Flannery and Rangan (2002) document a build-up of regulatory and market equity capital in large U.S. bank holding companies from 1986 and 2000, beyond levels necessary to meet regulatory standards, and attribute this increase in capital to enhanced market incentives to monitor and price large banks' default risk. Barrios and Blanco (2003) argue that Spanish banks' capital ratios over the period 1985–1991 were primarily driven by the pressure of market forces rather than regulatory constraints.

[9]Institutions with a deposit/asset ratio above 20 percent and a loan/asset ratio above 10 percent, as in Beltratti and Stulz (forthcoming).

data are from the Bankscope database, which has good coverage from 2004 onwards, and the stock return data is from Datastream. We discard obvious mistakes in the data as well as outliers at the 1 percent and 99 percent levels.

Banks performed poorly over the crisis, with an average stock return of −42 percent from June 30, 2007 to December 30, 2008, as shown in Table 4.1. The recent financial instability originating from concerns about the sovereign debt of Eurozone countries has also been accompanied by poor performance of banks. Their average stock return was −13 percent over the three month period from June 30, 2011 to September 30, 2011. In both cases, the standard deviations of the returns are quite large, showing a large variation in bank performance during periods of instability.

Table 4.1: Descriptive statistics – bank stock returns over periods of crisis

	June 2007 to Dec 2008 (769 obs)	June 2011 to Sep 2011 (804 obs)
Mean	-41.67	-13.15
Std. Dev.	31.09	19.59
Min	-99.97	-75.28
Max	62.59	192.36

Table 1 shows summary statistics for the stock returns of the banks in the sample for two periods: (1) June 30, 2007 to December 30, 2008 corresponding to the subprime crisis, and (2) June 30, 2011 to September 30, 2011 corresponding to the Eurozone sovereign debt crisis.

Our first hypothesis is that banks with higher risk-weighted assets will perform worse during a period of crisis. This would be an indication that markets do give credence to the regulatory measure of asset-risk. In other words, investors expect banks with higher RWA to have larger *LGD*s during the financial crisis. We separate banks' regulatory capital ratios into simple leverage ratios and RWA scaled by tangible assets, to determine the effects of RWA on stock returns while controlling for the capital of the bank.[10]

H1 *Banks with lower RWA performed better during the crisis.*

Second, we expect a positive relationship between capital and stock returns, since capital functions as a buffer against adverse shocks by providing loss absorbency beyond provisions and other expected-loss buffers. A higher share of customer deposits in funding decreases the susceptibility of banks to runs, so we expect banks with more stable funding to perform better during periods of crisis. There may also be a trade-off between these two factors, in that banks with higher capital are better able to withstand funding problems.

H2 *Banks with higher capital ratios will had higher stock returns during the crisis and banks with more stable funding had higher stock returns during the crisis.*

H2a *Banks with more stable funding did not receive as high a reward for higher capital, compared to banks with less stable funding.*

Third, if RWA are a good measure of asset-risk, we expect they will be positively related to market-based measures of risk. The relationship between

[10]For example: $\frac{Tier1Capital}{RWA} = \frac{Tier1Capital}{TangibleAssets} \times \frac{TangibleAssets}{RWA}$. Previous studies include either the regulatory capital ratio or the simple leverage ratio, which does not allow for a direct test of the effect of RWA on performance.

the two, if found, could change in either direction after the crisis. The onset of the crisis could render RWA less credible to investors, or the increase in risk-aversion associated with crisis could result in increased sensitivity to any available information on asset-risk.

H3 *Market measures of bank risk will be positively correlated with RWA.*

We estimate two models to test these hypotheses. In the first, we focus on the effects of risk-weighted assets and capital adequacy on the cross-section of banks' stock returns, while controlling for other balance-sheet measures of risk exposure. We perform OLS estimation of equation 4.1:

$$r_i = \theta_0 + \theta_1 (RWA/TA)_{i,t-1} + \theta_2 (Capital/TA) + X_{i,t-1}\gamma_1 + \nu_t \tag{4.1}$$

where the dependent variable r_i is the real stock return in US dollars from June 30, 2007 to December 30, 2008 for bank i. This is the period over which there was a sharp decline in aggregate stock market indexes.[11] We also study stock returns over the three-month period from June 30, 2011 to Sep 30, 2011 to compare market reactions in the recent European sovereign debt crisis to the first phase of the global financial crisis. In both cases, all of the explanatory variables are lagged by one year.

[11]The U.S. Department of the Treasury established the Troubled Assets Relief Program, in which they infused capital into qualifying financial institutions, in October 2008. This may have had an effect on bank's stock returns unrelated to underlying soundness of banks. For this reason we estimate equation (1) using the period preceding TARP, from June 20, 2007 to September 30, 2008, as a robustness check and find the results to be quantitatively similar.

The main explanatory variables of interest are the ratio of risk-weighted assets to tangible assets and the capital ratio.[12] We use tangible common equity (total equity minus preferred shares, intangibles, and goodwill) as our measure of bank capital in most specifications as one can expect holders of non-TCE capital instruments to have had weaker incentives to monitor bank risk-taking than common equity shareholders in the run up to the recent financial crisis.

The other explanatory variables, in $X_{i,t-1}$, are:

- i Stability of funding, measured as the share of customer deposits in total deposits and short-term funding[13]
- ii The ratio of securities to assets
- iii The share of non-performing loans
- iv Return on average assets, a measure of the bank profitability
- v The log of assets, to proxy for bank size
- vi Country dummies, to control for differences in the institutional and regulatory environments across countries

[12] Three different measures of capital are (i) tangible common equity, (ii) Tier 1 regulatory capital, and (iii) Total regulatory capital. Tier 1 capital consists of shareholder's funds, perpetual non-cumulative preference share, and retained earnings. Tier 2 capital includes hybrid capital, subordinated debt, loan loss reserves, and valuation reserves. Total regulatory capital is equal to the sum of Tier 1 capital and Tier 2 capital. After comparing three different measures of capital in our first specification, we proceed to use tangible common equity (total equity minus preferred shares, intangibles, and goodwill from total equity, where the data is available) as our measure of bank capital in the rest of the paper.

[13] This is equal to $100 - x$ where x is the funding fragility measure of Demirguç-Kunt and Huizinga (2009): deposits from other banks, other deposits, and short-term borrowing as a fraction of total deposits plus money market funding.

vii Dummy variables to control for the business model of the bank[14]

Table 4.2 reports descriptive statistics for the explanatory variables in 2006 and 2010.

Table 4.2: Descriptive statistics – explanatory variables

	2006 (769 obs)		2010 (804 obs)	
	Mean	Std. Dev.	Mean	Std. Dev.
RWA/TangibleAssets	41.89	31.67	66.38	14.87
TCE/TangibleAssets	7.92	5.41	7.04	3.93
Tier 1 Capital/TangibleAssets	9.01	5.01	8.69	3.49
Total Capital/TangibleAssets	6.31	6.60	9.93	3.57
CustDeposits	90.44	12.05	91.15	11.31
Securities/Assets	20.26	11.86	22.20	11.88
NPL/Loans	1.66	2.72	4.41	4.78
ROAA	0.88	0.85	0.37	1.17
Assets - millions USD	55,900	228,000	83,764	316,632
Beta	0.24	1.06	1.00	1.33

The variables are the ratio of risk-weighted assets to tangible assets, capital ratios (tangible common equity (TCE)), Tier1 Capital, and Total regulatory capital, all divided by tangible assets (TA)), the share of stable (customer) deposits, the share of securities in the bank's assets, the share of non-performing loans (NPL), the return on assets, assets, and the bank's stock's beta with a national market index.

The share of customer deposits in total deposits is expected to increase a bank's stability since these deposits are less likely to be withdrawn in a bank run, due to deposit insurance.[15] Gorton (2010) and others have described

[14]Bank holding companies, commercial banks, cooperative banks, investment banks, real estate and mortgage banks, and savings banks

[15]Our measure is equal to 100 – x where x is the funding fragility measure of Demirguç-

the recent crisis as a run in non-retail funding markets. We expect a positive relationship between the stability of funding and banks' stock returns.

A second specification of this model includes an interaction term between the capital ratio and funding stability. This is to test the notion that there is a trade-off in the capital adequacy and funding required to satisfy markets of a bank's health. A negative coefficient on the interaction term between funding stability and the capital ratio suggests that banks with more stable funding are not required to hold as much capital in order to receive the same stock return, compared to a banks with fragile funding.

The second model is a panel estimation of how the explanatory variables described above are related to banks' systematic risk – beta from a Capital Asset Pricing Model (CAPM). We perform a panel estimation of equation 4.2 over the period from 2004 to 2010:

$$Risk_i = \mu_j + \delta_1(RWA/TA)_{i,t-1} + \delta_2(Capital/TA) + X_{i,t-1}\gamma_1 + \nu_{i,t} \quad (4.2)$$

The explanatory variables are as in equation 4.1 and we alternately include country fixed effects, to control for time-invariant country-specific factors that may affect bank systematic risk, and bank fixed effects, to study the dynamic relationship between bank systematic risk and RWA. We also include year dummies to control for macroeconomic shocks that may affect bank stock returns. The dependent variable, $Risk_{i,t}$, is the coefficient β from

Kunt and Huizinga (2009).

the following model:

$$r_{it} - r_{ft} = \alpha_i + \beta(r_{Mt} - r_{ft}) + \beta_W(r_{Wt} - r_{ft}) + \epsilon_{it} \tag{4.3}$$

estimated over the previous 60 month period. Nominal stock prices in US dollars are deflated by the CPI to obtain real returns, $r_{f,t}$ is the 3-month US Treasury bill rate adjusted to a one month risk-free rate, $r_{M,t}$ is the MSCI national market index for the country M in which bank i is headquartered, and $r_{W,t}$ is the MSCI World index. That is, for each bank-year observation in model 4.3, β is estimated using monthly, US-dollar, real excess returns over the last 5 years.

4.6 Results and Discussion

4.6.1 Determinants of stock returns

Market perceptions of risk-weighted assets

Table 4.3 presents the results of our benchmark estimation of equation 4.1, the determinants of stock returns over 2007-2008 crisis period. As expected, we find that stock returns are lower for banks with higher risk-weighted assets. The estimated coefficient in column (1) indicated that banks with a one percentage point higher RWA to tangible assets ratio have a stock return that is 0.075 percent lower. The estimated coefficients on the three different capital ratios are not statistically significant but their magnitudes are consistent with the finding of Demirguç-Kunt, Detragiache, and Merrouche (2010) that certain types of capital matter more in explaining stock returns. The signs of the coefficients on the additional explanatory variables are as expected. Higher stock returns are associated with more stable funding, more securities holdings, a lower share of non-performing loans, and a higher accounting return on assets. However, only the share of securities to assets, and the accounting return on assets have a strong statistical relationship with the stock returns.

Table 4.4 shows the same estimation on the sample restricted to larger banks, with assets greater than 50 billion US dollars in 2006. The coefficient on RWA is also negative and statistically significant in this sample. Large banks with a 1 percent point higher RWA to tangible assets ratio have a 0.39 percent lower stock return, on average. Large banks are different than the rest of the sample in that access to stable short term funding seems to be more important for them than securities holdings. The coefficient on funding stability is now statistically significant while the coefficient on the ratio of securities in assets is not. A one percentage point increase in the share of stable funding at a large bank is associated with a stock return that is 0.63 percent higher, on average. As with the whole sample, higher net income as indicated by a higher ROAA, is rewarded with a higher stock return.

Table 4.3: Determinants of returns – Do risk-weighted assets affect stock returns?

Dependent variable: Crisis stock return

	(1)	(2)	(3)
RWA/TangibleAssets	-0.075***	-0.054	-0.065**
	(0.027)	(0.033)	(0.027)
TCE/TangibleAssets	0.066		
	(0.195)		
Tier1capital/TangibleAssets		-0.307	
		(0.209)	
TotalCapital/TangibleAssets			-0.065
			(0.184)
CustDeposits	0.122	0.101	0.126
	(0.087)	(0.093)	(0.089)
Securities/Assets	0.759***	0.783***	0.763***
	(0.116)	(0.106)	(0.120)
NPL/Loans	-0.338	-0.359	-0.349
	(0.216)	(0.226)	(0.226)
ROAA	6.052***	5.542***	5.815***
	(0.707)	(0.678)	(0.678)
log(Assets)	-0.032	-0.510	-0.120
	(1.277)	(1.306)	(1.139)
Beta	-0.069	0.018	-0.031
	(0.805)	(0.796)	(0.786)
Observations	769	762	769
Adj R-squared	0.210	0.209	0.210

The table presents regressions for banks in 32 countries. The dependent variable is the bank's stock return over the period from June 30, 2007 to December 30, 2008. The independent variables, all values for 2006, are the ratio of risk-weighted assets to tangible assets, capital ratios (tangible common equity (TCE)), Tier1 Capital, and Total regulatory capital, all divided by tangible assets), the share of stable deposits, the share of securities in the bank's assets, the share of non-performing loans, the return on assets, the log of assets, and the stock's beta with a national market index. Country dummy variables and dummy variables representing the bank's business model are included. Standard errors (in parentheses below the coefficient estimates) are adjusted for heteroskedasticity following Huber (1967) and White (1980), and generalized for clustering at the country level. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels, respectively.

Table 4.4: Determinants of returns – Do risk-weighted assets affect stock returns of large banks?

Large banks: Assets>50 Billion US$
Dependent variable: Crisis stock return

	(1)	(2)	(3)
RWA/TangibleAssets	-0.388***	-0.448***	-0.678*
	(0.108)	(0.127)	(0.353)
TCE/RWAfloor	-0.559		
	(1.430)		
Tier1capital/RWAfloor		1.666	
		(2.463)	
TotalCapital/RWAfloor			2.264
			(2.670)
CustomerDeposits	0.625**	0.532**	0.578**
	(0.272)	(0.217)	(0.223)
Securities/Assets	0.100	0.090	0.019
	(0.303)	(0.304)	(0.312)
NPL/Loans	0.692	1.161	0.936
	(1.516)	(1.654)	(1.466)
ROAA	21.200***	18.980***	18.323***
	(6.519)	(6.567)	(6.539)
log(Assets)	-0.627	-0.189	-0.222
	(2.760)	(2.879)	(2.851)
Beta	0.175	-0.221	-0.441
	(3.451)	(3.472)	(3.415)
Observations	90	90	90
Adj R-squared	0.595	0.597	0.598

The table presents regressions for large banks in 32 countries – those with total assets greater than 50 billion US dollars in 2006. The dependent variable is the bank's stock return over the period from June 30, 2007 to December 30, 2008. The independent variables are as in Table 4.3.

Is there a capital-funding trade-off?

We find a trade-off between capital and funding in terms of their positive effects on bank stock returns. Table 4.5 presents the results of the estimation of model 4.1 in which an interaction term between capital and funding stability is included. The negative coefficient on the interaction term in column (2) shows that the more stable a bank's funding, the less positive the effect of higher capital on its stock return. Column (3) indicates that this trade-off exists for large banks as well.

Differences by Basel credit risk measurement method

At the time of the subprime crisis, countries had made different degrees of progress towards becoming following Basel II guidelines. The EU Capital Requirements Directive required that countries in the European Union implement the Basel II guidelines by the time of the crisis, generally initially following the standardized approach to measuring credit risk, while many countries were still following Basel I guidelines. Table 4.6 shows the dates of implementation of the Basel II approaches (standardized and advanced approaches) in different countries.

We investigate whether the relationship between stock returns and RWA is the same for banks in Basel I and Basel II countries by adding a country-level indicator variable for counties that had moved to the Basel II Standardized Approach by the time of the crisis, as well as interaction between the indicator and RWA/TA, to equation (1) 4.1. We also include dummy variables for each region, North America, Europe, and Asia, in these specifications and, in order to ensure that the results are not being driven by differences in accounting methods, we also include indicator variables to control for the accounting regime being followed by each bank.[16]

The results are presented in Table 4.7. Column (2) shows that for the whole sample, there is no significantly different effects of RWA/TA on returns for banks in countries that were Basel II compliant. For large banks, however, the negative relationship between RWA and returns is significantly smaller when banks are in Basel II countries.

The results presented in this section are robust to using the stock return from June 30, 2007 to September 30, 2008, the phase of the financial crisis before the beginning of government capital purchase programs, as the dependent variable.

[16]Le Leslé and Avramova (2012) note that a key difference between the International Financial Reporting Standards (IFRS) and the US Generally Accepted Accounting Principles (GAAP) is that the relevant off-balance-sheet assets can be calculated net of derivatives in the GAAP, suggesting RWA would be lower under GAAP than under IFRS, all else equal. They find, however, that RWA do not appear to be different across different accounting methods in a sample of fifty internationally active banks in 25 countries.

Table 4.5: Determinants of returns – Is there a capital-funding trade-off?

Dependent variable: Crisis stock return

	(1) All banks	(2) All banks	(3) Large banks
RWA/TangibleAssets	-0.075***	-0.088**	-0.339***
	(0.027)	(0.034)	(0.116)
TCE/TangibleAssets	0.066	3.710*	4.636*
	(0.195)	(2.124)	(2.497)
CustDeposits	0.122	0.395**	0.878***
	(0.087)	(0.170)	(0.288)
(TCE/TangibleAssets)*CustDeposits		-0.039*	-0.072**
		(0.021)	(0.035)
Securities/Assets	0.759***	0.739***	0.165
	(0.116)	(0.120)	(0.307)
NPL/Loans	-0.338	-0.322	2.421
	(0.216)	(0.201)	(1.896)
ROAA	6.052***	4.947***	19.127***
	(0.707)	(0.671)	(5.890)
log(Assets)	-0.032	0.366	-1.301
	(1.277)	(1.262)	(2.623)
Beta	-0.069	0.049	0.851
	(0.805)	(0.692)	(3.411)
Observations	769	769	90
Adj R-squared	0.210	0.213	0.609

The table presents regressions for banks in 32 countries. The dependent variable is the bank's stock return over the period from June 30, 2007 to December 30, 2008. Columns (1) and (2) present the whole sample, and column (3) present results for the sample of large banks – banks with assets greater than 50 billion US dollars in 2006. The independent variables are as in Table table:rwareg1 and additionally include an interaction term between the capital ratio (TCE/tangible assets) and stable deposits.

Table 4.6: Basel II implementation schedules – credit risk measurement

	Standardized approach	Advanced approaches
Australia	Jan 2008	Jan 2008
Austria	Jan 2007	Jan 2008
Belgium	Jan 2007	Jan 2008
Canada	Nov 2007	Nov 2007
China	NA	2011-2013
Denmark	Jan 2007	Jan 2008
Finland	Jan 2007	Jan 2008
France	Jan 2007	Jan 2008
Germany	Jan 2007	Jan 2008
Greece	Jan 2007	Jan 2008
Hong Kong	Jan 2007	Jan 2007
India	April 2007	post Dec 2011
Indonesia	Jan 2009	Oct 2010
Italy	Jan 2007	Jan 2008
Japan	March 2007	March 2008
Korea	Dec 2007	Dec 2007
Malaysia	Jan 2008	Jan 2010
Norway	Jan 2007	Jan 2008
Philippines	Jul 2007	post 2010
Poland	Jan 2007	Jan 2008
Russian Federation	Jul 2012	NA
Singapore	March 2007	Jan 2008
Spain	Jan 2007	Jan 2008
Sri Lanka	Jan 2008	post 2010
Sweden	Jan 2007	Jan 2008
Switzerland	Jan 2007	Jan 2008
Taiwan	end 2006	NA
Thailand	Jan 2009	Jan 2009
Turkey	June 2011	NA
Ukraine	NA	NA
UK	Jan 2008	Jan 2008
USA	NA	mid-2009 for 'core banks'

NA=not announced

Sources: Supervisory agency websites and surveys,and IMF Financial Stability Assessment Program Reports.

'Core banks' are those that have consolidated total assets $\geq$ \$250 billion, consolidated on-balance-sheet foreign exposure $\geq$ \$10 billion, or are subsidiaries of a core bank.

Table 4.7: Determinants of returns – Basel I versus Basel II standardized approach to measuring RWA

Dependent variable: Crisis stock return

	(1) All banks	(2) All banks	(3) Large banks
Basel II indicator		2.946	-29.371**
		(8.461)	(12.939)
RWA/TA	-0.077**	-0.108***	-0.435***
	(0.029)	(0.024)	(0.089)
Basel II * RWA/TA		0.067	0.430**
		(0.075)	(0.198)
TCE/TA	-0.175	-0.110	-0.214
	(0.347)	(0.278)	(1.274)
CustDeposits	0.255*	0.257*	0.527***
	(0.147)	(0.135)	(0.193)
Securities/Assets	0.661***	0.634***	0.187
	(0.179)	(0.197)	(0.204)
NPL/Loans	-0.336	-0.213	-0.787
	(0.361)	(0.288)	(1.110)
ROAA	4.048**	4.268**	10.970*
	(1.852)	(1.621)	(5.889)
log(Assets)	-0.274	-0.204	-0.818
	(1.183)	(1.222)	(2.239)
Beta	-0.453	-0.371	-2.014
	(1.018)	(0.909)	(2.644)
Observations	769	769	90
Adj R-squared	0.151	0.153	0.422

The table presents regressions for banks in 32 countries. The dependent variable is the bank's stock return over the period from June 30, 2007 to December 30, 2008. Columns (1) and (2) present the whole sample, and column (3) present results for the sample of large banks – banks with assets greater than 50 billion US dollars in 2006. The independent variables are an indicator variable for countries that use the Basel II Standardized Approach to calculating RWA, and an interaction with the bank's RWA to tangible assets, the capital ratios (tangible Common Equity (TCE) divided by tangible assets (TA)), the share of stable deposits, the share of securities in the bank's assets, the share of non-performing loans, and the return on assets. The log of assets, the stock's beta with a national market index, regional dummies, and dummy variables representing the bank's business model are included in each specification.

4.6.2 Market risk and balance-sheet measures of risk exposure

This section presents the results of estimating equation (3.2), to study the relationship between a bank systematic risk and RWA. Column (1) of Table 4.8 presents the estimation results for the period from 2004 to 2010, including country fixed effects. There is no significant relationship between systematic risk and RWA. After including bank fixed effects in column (2), however, the estimated coefficient on RWA/TA is positive and significant. In the first instance we controlled for time-invariant country-specific unobservables, while the specification with bank fixed effects controls instead for any bank-level unobserved variables that do not vary over time. Thus, it appears there is no static relationship where banks with higher RWA have greater systematic risk, but instead, banks with higher RWA have greater systematic risk over time. The coefficient of 0.005 in column (2) suggests that a one standard deviation increase corresponds to a 0.12 standard deviation increase in systematic risk. Turning to the coefficients on the control variables, we see that the factors that are positively related to stock return performance are negatively related to systematic risk, as expected.

We next split the sample into two periods, the three years prior to the start of the crisis from 2004 to 2006 and three after the onset from 2008 to 2010, and estimate model (3.2) on both samples to investigate whether there is a change in the factors that affect systematic risk. Shown in Table

4.9, the Chow test rejects the hypothesis that the relationship is the same before and since the crisis for several explanatory variables: the RWA ratio, the share of securities in assets, non-performing loans, and return on assets. The relationship between RWA/TA and systematic risk is positive before the crisis, but negative since the crisis.

Table 4.8: Market risk and balance-sheet measures of risk exposure

Panel 2004-2010

Dependent variable: Systematic Risk (\beta)

	(1)	(2)	(3)	(4)
	All banks	All banks	Large banks	Large banks
RWA/TangibleAssets (t-1)	0.001	0.005***	0.001	0.003
	(0.017)	(0.119)	(0.031)	(0.077)
TCE/TangibleAssets (t-1)	0.009	0.023*	-0.052**	-0.109**
	(0.037)	(0.096)	(-0.170)	(-0.360)
CustDeposits (t-1)	-0.001	-0.003	-0.004	0.005
	(-0.012)	(-0.028)	(-0.091)	(0.109)
Securities/Assets (t-1)	-0.009***	-0.000	0.001	0.014*
	(-0.088)	(-0.005)	(0.010)	(0.260)
NPL/Loans (t-1)	0.026***	0.032***	0.041**	0.106***
	(0.063)	(0.079)	(0.114)	(0.295)
ROAA (t-1)	-0.066***	-0.070***	-0.022	-0.030
	(-0.059)	(-0.062)	(-0.023)	(-0.031)
log(Assets) (t-1)	0.274***	0.157	0.071	-0.653**
	(0.502)	(0.287)	(0.113)	(-1.039)
Year dummies	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No
Bank fixed effects	No	Yes	No	Yes
Observations	4280	4280	563	563
Adj R-squared	0.217	0.184	0.176	0.149

The table presents panel regressions for banks in 32 countries from 2004 to 2010. The dependent variable is the stock's beta with a national market index estimated from a CAPM model. The independent variables, all lagged by one year, are as in Table 4.3. Additionally, each specification includes dummy variables for each year. Columns (1) and (3) include country fixed effects and dummy variables representing the banks' business model, and columns (2) and (4) include bank-level fixed effects.

Table 4.9: Market measures of risk and balance-sheet measures of risk exposure – have the relationships changed since the crisis?

Risk pre and post-crisis

Dependent variable: Systematic Risk (\beta)

	(1) 2004-2006	(2) 2008-2010	*p* value for test: coeff (1) = coeff (2)
RWA/TangibleAssets (t-1)	0.006***	-0.002***	0.000
	(0.116)	(-0.067)	
TCE/TA (t-1)	0.016***	-0.001	0.140
	(0.068)	(-0.003)	
CustDeposits (t-1)	-0.004	0.005	0.034
	(-0.126)	(0.193)	
Securities/Assets (t-1)	-0.003***	-0.015***	0.001
	(-0.029)	(-0.150)	
NPL/Loans (t-1)	0.031	-0.026**	0.072
	(0.050)	(-0.053)	
ROAA (t-1)	0.015	-0.107***	0.000
	(0.008)	(-0.073)	
log(Assets) (t-1)	0.148***	0.212	0.630
	(0.836)	(1.296)	
Constant	-1.934***	-2.106	0.927
	(-0.721)	(-0.830)	
Observations	4280		
Adj R-squared	0.328		

Standardized coefficients are reported in parentheses. The table presents panel regressions for banks in 32 countries from 2004-2006 in Column (1) and 2008-2010 in Column (2). The dependent variable is the stock's beta with a national market index estimated from a CAPM model. The independent variables, all lagged by one year, are as in 4.3. Country fixed effects and dummy variables representing the bank's business model are included.

4.7 Performance during the Eurozone debt crisis

We check the robustness of the negative relationship between bank stock returns and RWA in this section, by estimating equation 4.1 for a recent period of financial instability – the Eurozone sovereign debt crisis. We find that the negative relationship between RWA and stock returns is robust to the different time period.

Table 4.10 shows the results of model (3.1) estimated for the period from June 30, 2011 to September 30, 2011. The signs of the coefficients are the same as for model 4.1 estimated over 2007-2008 crisis period, however only RWA/TA, return on assets, and bank size had a statistically measurable effect on the stock returns in this period.

Next, we differentiate between the method used to calculate credit risk, similar to Table 4.7 presented above for the subprime crisis. By 2010, banks in several countries had moved towards using one of the Basel II advanced approaches to measuring credit risk (FIRB or AIRB), while many were using the Basel II standardized approach (SA), and some were still following Basel I guidelines. The estimated coefficients on Basel II SA*RWA/TA in Table 4.11 suggests that the relationship between RWA and returns is less negative for banks using the Basel II SA, compared to those using Basel I. The relationship is not significantly different for banks following one of the advanced approaches.

Table 4.10: Determinants of returns – performance during the European sovereign debt crisis

Dependent variable: Stock return from June 2011 to Sep 2011

	(1) All banks	(2) Excluding US	(3) Large banks
RWA/TangibleAssets	-0.095+	-0.243***	-0.026
	(0.057)	(0.068)	(0.166)
TCE/TangibleAssets	-0.021	0.424	0.759
	(0.070)	(0.359)	(1.491)
CustDeposits	0.039	0.024	-0.064
	(0.046)	(0.071)	(0.112)
Securities/Assets	0.052	-0.031	0.018
	(0.035)	(0.076)	(0.145)
NPL/Loans	-0.254	-0.053	-0.221
	(0.187)	(0.179)	(0.737)
ROAA	2.584***	1.101	6.305*
	(0.284)	(0.937)	(3.146)
log(Assets)	-2.977***	-1.704**	-4.024*
	(0.440)	(0.624)	(2.359)
Beta	-0.254	-2.456	-1.409
	(0.204)	(3.069)	(1.626)
Observations	804	304	129
Adj R-squared	0.363	0.722	0.707

The table presents regressions for banks in 32 countries. The dependent variable is the bank's stock return over the period from June 30, 2011 to September 30, 2011. The independent variables, all values for 2010, are the ratio of risk-weighted assets to tangible assets, the capital ratio (tangible common equity (TCE) to tangible assets (TA)), the share of stable deposits, the share of securities in the bank's assets, the share of non-performing loans, the return on assets, the log of assets, and the stock's beta with a national market index. Country dummies and dummy variables representing the bank's business model are included in each specification. Column (1) presents the whole sample of banks, column (2) the sample excluding banks based in the United States, and column (3) the banks with total assets greater than 50 billion US dollars in 2010.

Table 4.11: Determinants of returns during the European sovereign debt crisis – Basel I versus Basel II approaches to measuring RWA

Dependent variable: Stock return from June 2011 to Sep 2011

	(1) All banks	(1) All banks	(2) Excluding US
Basel II SA indicator		-28.565**	-37.732**
		(11.211)	(15.532)
Basel II Advanced indicator		14.742	2.630
		(11.506)	(11.950)
RWA/TA	-0.217**	-0.216+	-0.533***
	(0.101)	(0.129)	(0.162)
Basel II SA * RWA/TA		0.228*	0.406*
		(0.130)	(0.213)
Basel II Advanced * RWA/TA		-0.193	-0.076
		(0.152)	(0.176)
TCE/TA	-0.369***	-0.020	-0.170
	(0.122)	(0.104)	(0.351)
CustDeposits	0.268**	0.194***	0.592***
	(0.102)	(0.062)	(0.079)
Securities/Assets	0.094*	0.106**	0.039
	(0.051)	(0.051)	(0.098)
NPL/Loans	-0.301	-0.227	-0.199
	(0.188)	(0.161)	(0.141)
ROAA	1.706**	2.625***	2.592
	(0.633)	(0.256)	(1.596)
log(Assets)	-2.759***	-3.985***	-4.245***
	(0.580)	(0.483)	(0.725)
Beta	0.020	0.141	0.693
	(0.145)	(0.121)	(2.095)
Observations	767	767	304
Adj R-squared	0.249	0.314	0.423

The table presents regressions for banks in 32 countries. The dependent variable is the bank's stock return over the period from June 30, 2011 to September 30, 2011. The independent variables include: an indicator variable representing countries where banks predominantly use the Basel II Standardized Approach to calculating RWA, an indicator variable for countries where banks predominantly use one of the Basel II Advanced IRB approaches, and interactions between these indicators and RWA/TA. The remaining independent variables are as in Table table:euroreg1and each specification includes regional dummies (for North America, Europe, or Asia), dummies representing bank business model, and dummy variables representing the accounting method.

4.8 Conclusion

There has been a steady decline in the measure of asset-risk that banks report to regulators – risk-weighted assets (RWA) – over the last decade. In light of this trend and other indications that banks may under-report RWA in an attempt to minimize the amount of capital they must hold, we study how equity market investors account for the riskiness of RWA by examining the determinants of stock returns and a stock-market measure of risk of an international panel of banks.

Regarding banking stock returns, we find a negative relationship between RWA and stock returns over periods of financial crisis, suggesting that investors use RWA as an indicator of bank portfolio risk. Banks with higher risk-weighted assets performed worse both during the subprime crisis and a recent period of stock market decline accompanying the Eurozone sovereign debt crisis. Comparing regions with different regulatory structures, we find evidence that the relationship between stock returns and RWA is weaker in countries where banks have more discretion in the calculation of RWA. Specifically, in countries that had implemented Basel II before the onset of the recent financial crisis, primarily following the standardized approach to measuring credit risk, the relationship between stock returns and RWA is less negative or even positive. In addition, we find a trade-off between capital and funding in terms of their positive effects on bank stock returns. The more stable a bank's funding, the less positive the effect of capital on its stock return.

We also study a market measure of risk, the bank's systematic risk, or beta, from 2004 to 2010. We find no static relationship between RWA and systematic risk across banks, however, we find evidence of a dynamic effect where systematic risk increases for those banks whose RWA increases. Finally, there is evidence of a change in the relationship between systematic risk and RWA since the start of the crisis. The positive relationship between RWA and market risk in the three years prior to the crisis, from 2004 to 2006, becomes negative, albeit small in magnitude, after the crisis.

In light of increasing risk-aversion in markets during times of crisis, the question of how market assessments of risk should be incorporated into banking regulation and supervision remains. Indeed, the asymmetry of information between banks, supervisors, and market participants regarding how risky RWA are can lead to increased uncertainty about the adequacy of bank capital which, during a financial crisis, can have damaging effects for financial stability.

4.9 Appendix

Table 4.12: List of countries – full sample

Country	# banks	% Sample	Country	# banks	% Sample
Australia	6	0.75	Norway	14	1.74
Austria	4	0.5	Philippines	11	1.37
Belgium	2	0.25	Poland	10	1.24
Canada	10	1.24	Russian Federation	8	1
China	11	1.37	Singapore	4	0.5
Denmark	11	1.37	Spain	8	1
Finland	2	0.25	Sri Lanka	5	0.62
France	4	0.5	Sweden	4	0.5
Germany	5	0.62	Switzerland	3	0.37
Greece	8	1	Taiwan	9	1.12
Hong Kong	6	0.75	Thailand	6	0.75
India	12	1.49	Turkey	10	1.24
Indonesia	8	1	Ukraine	2	0.25
Italy	20	2.49	UK	7	0.87
Japan	81	10.07	USA	500	62.19
Korea	4	0.5			
Malaysia	9	1.12			

Table 4.13: Descriptive statistics – correlations of explanatory variables

Correlations of explanatory variables in 2006 (762 observations)

	RWA/TA	TCE/TA	Tier1/TA	TotalCap/TA	CustDeps	Sec/Assets	NPL/Loans	ROAA	log(Assets)	Beta
RWA/TA	1									
TCE/TA	0.141	1								
Tier 1 Capital/TA	0.084	0.948	1							
Total Capital/TA	0.742	0.689	0.671	1						
CustDeposits	-0.064	0.268	0.249	0.055	1					
Securities/Assets	-0.097	-0.130	-0.161	-0.036	-0.227	1				
NPL/Loans	0.240	-0.217	-0.229	0.088	-0.060	0.160	1			
ROAA	-0.127	-0.292	-0.309	-0.367	-0.096	-0.082	-0.073	1		
log(Assets)	0.153	-0.581	-0.592	-0.169	-0.494	0.313	0.292	0.152	1	
Beta	0.173	-0.173	-0.182	0.058	-0.206	0.088	0.218	0.050	0.3955	1

Correlations of explanatory variables in 2010 (804 observations)

	RWA/TA	TCE/TA	Tier1/TA	TotalCap/TA	CustDeps	Sec/Assets	NPL/Loans	ROAA	log(Assets)	Beta
RWA/TA	1									
TCE/TA	0.241	1								
Tier 1 Capital/TA	0.495	0.765	1							
Total Capital/TA	0.572	0.724	0.961	1						
CustDeposits	0.337	0.159	0.246	0.210	1					
Securities/Assets	-0.568	-0.045	-0.161	-0.194	-0.317	1				
NPL/Loans	0.138	-0.026	0.045	0.079	-0.061	-0.179	1			
ROAA	-0.076	0.224	0.046	0.054	-0.080	0.200	-0.392	1		
log(Assets)	-0.478	-0.360	-0.496	-0.426	-0.508	0.299	-0.107	0.1702	1	
Beta	0.018	-0.122	-0.044	-0.026	-0.043	0.024	0.009	-0.063	0.2672	1

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